Title of Dissertation:	EXPLAINING RESILIENCE TO PEER INFLUENCE: THE ROLE OF DECISION-MAKING
	Jessica R. Deitzer, Doctor of Philosophy, 2020
Dissertation Directed By:	Professor Jean Marie McGloin, Department of Criminology and Criminal Justice

Researchers often discuss deviant peers as if they are a deterministic risk for an adolescent's own delinquency. There is a strong, consistent link between the two, especially in adolescence. Yet, some adolescents act counter to predictions and display resilience to deviant peer influence. Paternoster and Pogarsky's (2009) concept of thoughtfully reflective decision-making (TRDM) may add to our understanding of resilience to deviant peer exposure; individuals who make slow, deliberate decisions may be more likely to avoid the pitfalls associated with deviant peers, perhaps by selecting out of deviant social networks.

In this dissertation, I use longitudinal data from the PROSPER Peers project in the context of adolescents in rural schools to 1) identify and describe a group of youth that displays resilience to deviant peer influence and 2) investigate whether decision-making skills differentiate those who demonstrate resilience from those who do not. I leverage structural equation modeling (SEM) to examine the role of TRDM

in fostering resilience to deviant peer influence. Specifically, I test whether TRDM moderates the impact of deviant peer exposure on resilience directly or indirectly, through prompting changes to the adolescents' social networks. I estimate SEM models that test these relationships using interaction and multigroup models separately for each starting wave.

I find evidence that TRDM promotes resilience to deviant peer influence across waves. My results also provide evidence of a nonlinear interaction between deviant peer exposure and TRDM, whereby TRDM is most protective for adolescents with a high degree (but not entirely) deviant peer group in for analyses starting in 6th or 7th grade. I do not find evidence of a consistent association between TRDM and a change in adolescents' proportion of deviant peers at the next wave or any partial or full reduction to the direct impact of TRDM on resilience when including this indirect pathway. Thus, I conclude that TRDM does not appear to have an indirect impact on resilience through prompting prosocial change to adolescents' friend groups. Finally, I discuss the limitations of my study, along with its implications for theory, practice, and future research.

EXPLAINING RESILIENCE TO PEER INFLUENCE: THE ROLE OF DECISION-MAKING

by

Jessica Rae Deitzer

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2020

Advisory Committee:
Professor Jean Marie McGloin, Chair
Associate Professor Bianca E. Bersani
Associate Professor María B. Vélez
Assistant Professor Wade Jacobsen
Professor Jeff Lucas, Dean's Representative

Acknowledgements

At the culmination of my PhD, it is encouraging to reflect on the many people who have guided me along the way. I am indebted to my chair, Jean McGloin, who has taken the time to invest in me, my career, and this dissertation. You have helped me become a better scholar and are an excellent embodiment of traits I want as a person. I will miss you (and Annie!) being right down the hall. To my mentor Heith Copes, thank you for going above and beyond with your time, guidance, and friendship throughout my path from unsure undergraduate to doctoral candidate. I am grateful to be one of your criminology minions.

This dissertation has benefitted from the comments of many bright, kind, and helpful committee members – Drs. Jean McGloin, Wade Jacobsen, Bianca Bersani, María Vélez, and Jeff Lucas – and other University of Maryland faculty and staff members too numerous to name. Special thanks to Wade Jacobsen for offering thoughtful perspectives, patiently answering questions, and connecting me with the PROSPER Peers project. Another big thank you to the friendships formed during this program, especially to my cohort-mate and confidant Lisa, without which these past five years would have been much, much harder.

This dissertation would not be possible without a support network that extends beyond academia. I would be remiss not to acknowledge my parents, Dave and Jackie, who taught me I could do anything I set my mind to with hard work, and my husband, Jon, who believed it. Jon, you have gone out of your way to support my aspirations, and I could not ask for a better life partner.

Table of Contents

List of Tables

List of Figures

CHAPTER 1: INTRODUCTION

Early research in criminology highlighted the group nature of crime (e.g., Breckinridge & Abbot, 1912; Shaw & McKay, 1942). This sparked early qualitative and correlational studies that consistently confirmed the relationship between having deviant friends and engaging in delinquency (Akers et al. 1979; Matsueda, 1982; Shaw, 1930; Short, 1957). Few areas of criminology have been subject to such extensive testing as the study of deviant peer influence, and it is now well established that deviant peers are one of the strongest and most consistent correlates of crime (McGloin & Thomas, 2019; Pratt et al., 2010; Warr, 2002). The connection between the delinquent behavior of peers and one's own delinquency is especially strong during adolescence, when adolescents prioritize their peers as social referents (Steinberg & Monahan, 2007; Warr, 2002). Yet, even the most robust research designs do not find deviant peers to be perfect predictors of crime, even among adolescents (see Gardner & Steinberg, 2005; Paternoster et al., 2013; Sacerdote, 2001), suggesting that some individuals display resilience to the influence of delinquent peers. The experiences of these "negative cases" who avoid demonstrating a delinquent outcome may be especially fruitful for understanding how to best combat deviant peer influence (Sullivan, 2011).

The existence of this "resilient" group has been underemphasized in criminological research on deviant peers thus far. Given the strength and consistency of findings on deviant peers, researchers often discuss them as if they are a deterministic risk for an adolescent's own delinquency. The strength of this relationship is so extolled that a major criticism of Sutherland is that he was too

deterministic in his explanation of the role of culture, including peers. More specifically, critics' claimed Sutherland and other learning theorists view socialization to be entirely successful, all of the time, with no room for departure from their group's expectations (Hirschi, 1996; Kornhauser, 1978). This is evident in Sutherland's work, as he often used causal language to describe the role of differential association in criminal behavior; for example, Sutherland introduced differential association theory by stating "the conditions that are said to cause crime should always be present when crime is present, and should always be absent when crime is absent" (Sutherland & Cressey, 1960, p. 74) and that "scientists strive to organize their knowledge in interrelated general propositions to which no exceptions can be found" (Sutherland et al., 1992, p. 86). Strong statements about the power of deviant peers continue to be echoed by other learning theorists – for example, Warr's (2002) statement that "criminal conduct is predominantly social behavior. Most offenders are embedded in a network of friends who also break the law, and the single strongest predictor of criminal behavior known to criminologists is the number of delinquent friends an individual has" (p. 3). In short, the way deviant peer influence is discussed rarely acknowledges heterogeneity in its impact. Instead, the way social learning theorists measure and model deviant peer influence typically assumes deviant peers will have a uniform impact on all.

Yet, just as Robins' (1978) famous paradox noted most delinquent children do not become delinquent adults even though most adult offenders were once delinquents, not all adolescents with deviant peers will become delinquent. Some adolescents may exhibit resilience to deviant peer influence, adapting positively

despite exposure to a highly delinquent peer group, thereby avoiding this common pathway to juvenile delinquency. Understanding the "negative cases" of youth who do not fit prediction and display resilience may shed light on the causal processes at play (Rutter, 2006; Sullivan, 2011). Likewise, the claim that differential association theory, along with today's social learning theory, is truly deterministic has been subject to some rebuttal (see Akers, 1990). Akers, founder of social learning theory in criminology, favors a "'soft behaviorism' that allows for choice and cognitive processes" (Akers, 1990, p. 666). In line with acknowledging the role of choice, I posit that a more accurate portrayal of deviant peer influence is one that acknowledges and strives to explain those who maintain resilience in the face of this risk factor. Examination of these "prosocial outliers" allows us to consider the full range of data rather than overwhelmingly focusing on the central tendency and refine theoretical models based on new information presented by these cases (Sullivan, 2011).

Resilience can be described as positive adaptation in the face of adverse circumstances such as trauma or risk factors associated with a specific negative outcome (Fergus & Zimmerman, 2005; Luthar, 2006). Early resilience researchers studied individual responses to naturally-occurring risk factors (e.g., experiencing the stressors of World War II, the Great Depression, or a death in the family) and found a subset of individuals that did not show the hypothesized negative outcomes. For example, Garmezy (1973) began his study of children at high risk for psychopathy (due to being the children of mentally ill parents) in the 40's and 50's. By the 1970's, he had discovered that some of the high-risk children had surprisingly good

developmental outcomes and began a new line of inquiry centered on explaining this phenomenon called Project Competence (Garmezy, 1987). After observing resilience across a variety of domains, psychologists began searching for the "missing links" to explain why some individuals may experience risk factors differently and even thrive in the face of significant challenges. This represented a notable departure from the focus on risk factors dominant in prior psychological studies.

Resilience is not a global personality trait that undergirds success across all life domains. Instead, it is typically referred to in domain-specific ways, with success in the outcome of interest defining the resilient group (Luthar, 2006). Resilience is not a general personality trait, which would suggest global positive outcomes for "resilient" individuals. For example, Luthar and colleagues have found that high-stress adolescents (from inner city environments with negative life events) who showed signs of behavioral resilience (social competence at school) still struggled with emotional adjustment, such as depression (Luthar, 1991; Luthar, Doernberger, & Zigler, 1993), which could cause trouble for other domains of resilience over time.

According to research on resilience, the presence of certain factors can protect individuals from or compensate for exposure to risk factors, aiding them in avoiding the negative outcomes (Sameroff, 2000). Those who display resilience may use environmental resources, such as positive ties to family, school, and the community, to overcome risks, but also personal assets, which are "positive factors that reside within the individual, such as competence, coping skills, and self-efficacy" (Fergus & Zimmerman, 2005, p. 399). A recent emphasis on the importance of social and environmental factors has led scholars to neglect these internal constructs (Kolar,

2011), which are more in-line with an agentic view of human nature. Assuming that risk factors can only be combated by other social and environmental factors neglects the important role of internal, personal assets, such as decision-making, in avoiding negative outcomes (Baron, 2004; McCarthy, 2002; Paternoster & Pogarsky, 2009). These personal assets are important as they may directly foster resilience, independent of external factors, and/or increase individual's resilience indirectly through leading the individual to make external changes to their environmental resources (Rutter, 1987, 2006).

In the context of deviant peers, resilience refers to the phenomenon of avoiding delinquency despite exposure to peer deviance. It is possible that some who avoid criminal behavior in the face of high deviant peer exposure acted intentionally according to their preferences to avoid the negative outcomes associated with the behavior of those around them (i.e. with agency; Paternoster & Pogarsky, 2009). Recent criminological work finds peer influence interacts with decision making concepts, including individual differences in traits and cognitive processes (Meldrum & Miller, 2013; Thomas & McGloin, 2013; Wright et al., 2004). Existing research on various decision-making concepts, including impulsivity, novelty seeking, and self-regulation, finds mixed results on whether these concepts can act as a protective or vulnerability factor for those exposed to deviant peers (Fergusson et al., 2007; Gardner et al., 2008; Thomas & McGloin, 2013). Some researchers find evidence of an interaction between decision-making skills and peer deviance that lessens or reverses the traditional impact of deviant peers; for example, Botvin and colleagues (1998) found while those with poor decision-making skills were more likely to

engage in drinking behaviors if their peers used alcohol, those with good decision-making skills were less likely to act similarly to their peers.

Decision-making skills thus may add to our understanding of resilience to deviant peer influence; particularly, those who make slow, thoughtful, deliberate decisions may be more likely to avoid the pitfalls associated with deviant peer influence or may be more likely to select out of deviant social networks. Paternoster and Pogarsky (2009) coined the term thoughtfully-reflective decision-making (hereafter TRDM) to refer to "the tendency of persons to collect information relevant to a problem or decision they must make, to think deliberately, carefully, and thoughtfully about possible solutions to the problem, apply reason to the examination of alternative solutions, and reflect back upon both the process and the outcome of the choice in order to assess what went right and what went wrong" (p. 104-5). The authors hypothesized the tendency to make decisions in this way would increase the likelihood of short and long-term success due to the ability to discern which behaviors will lead to the best outcomes. Indeed, engaging in a slow, reasoned decision-making process increased the likelihood that adolescents refrained from criminal and risky behaviors, graduated from college, and engaged in community and civic participation in later years (Paternoster & Pogarsky, 2009).

Although it has yet to be fully explored, decision-making skills may *directly* promote resilience to peer influence, as informed by the findings of Botvin and colleagues (1998). For example, individuals who engage in a more thoughtful process when deciding on action may be more likely to avoid increased impulsivity, risk preference, and present orientation in the face of deviant peer exposure and be less

likely to prioritize peers when making behavioral choices. These adolescents would be more likely to select prosocial behaviors that will have positive consequences in the long-term. Thus, undergoing a slow and reflective decision-making process may improve adolescent's outcomes in the presence of deviant peer influence (Paternoster & Pogarsky, 2009). At the same time, decision-making skills may *indirectly* promote resilience to deviant peer influence by encouraging selection into better social contexts, as thoughtful adolescents may recognize and seek to diminish the risks associated with having deviant friends.

According to Luthar (2006), personal assets with the highest "promotive potential" (or the most beneficial to resilience) are those that are "generative of other assets, catalyzing or setting into motion other strengths and mitigating vulnerabilities" (p. 781). Thus, the potential positive impact of personal assets does not negate the role of environmental assets, but encourages them; in this case, adolescents with positive decision-making skills do not just respond to their environment but also play a role in shaping their environment over time. Paternoster, Pogarsky, and Zimmerman (2011) accordingly found that TRDM was associated with building prosocial forms of human, social, and cultural capital, and these forms of capital somewhat explain the relationship between TRDM and better life outcomes. That is, those who make better decisions (a personal asset) tend to opt-in to positive environmental resources over time, likely recognizing the risks around them and making the decision to both improve their environment and their long-term outcomes.

In this dissertation, I use longitudinal self-report survey and social network data from the PROSPER (Promoting School-Community-University Partnerships to

Enhance Resilience) Peers project to 1) identify and describe adolescents who are resilient to high deviant peer exposure, 2) explore whether good decision-making skills promote resilience to deviant peer exposure directly or 3) indirectly, through adolescents making changes to their level of prosocial capital. This dataset is uniquely positioned to explore these subjects across stages in life where deviant peer influence is especially likely and impactful. For the current project, I conduct longitudinal structural equation models (SEM) to test my proposed models and examine how these processes differ across age groups.

The dissertation aims to fill gaps the existing literature in several ways. First, there is a now pressing need for research on peer influence to move beyond the question of whether peer influence matters and ask new questions (see Brechwald & Prinstein, 2011; McGloin & Thomas, 2019), such as what factors encourage imperviousness to deviant peer influence. Specifically, it expands the questions scholars are asking in the field of peer influence by focusing on for whom deviant peers do *not* appear to translate into delinquency. Literature in criminology overwhelmingly focuses on the negative impact of peers, ignoring the group that may resist the influence of deviant friends. Even the literature examining susceptibility or vulnerability to peer influence focuses on what factors make deviant peer influence more or less impactful, but neglects to focus on those for whom deviant peer influence may *not* be impactful. This group has the potential to inform our theoretical understanding of the factors that promote resilience to deviant peer influence and the factors that, when lacking, leave adolescents particularly susceptible to their influence.

Second, interventions designed to foster resilience amongst at-risk youth may be a more practical and effective choice than interventions aimed at reducing exposure to deviant peer influence or promoting desistance after the problem behaviors have manifested. Deviant peers are common and especially salient in adolescence. It is doubtful that any program could remove all deviant peers from a high-risk adolescent's social circle, especially as most adolescent's friend groups include at least some delinquent friends – for example, using a nationally representative sample, Haynie (2002) found that only 16% of adolescents around age 15 had no delinquent friends. As youth approach late adolescence, the average delinquency of the typical adolescent's friend group rises; this has been hypothesized to be the result of an increased desire for independence that manifests itself in the social mimicry of their consistently antisocial peers (see Moffit, 1993). Working instead to increase adolescent's resistance to peer influence presents a more feasible and effective alternative. Interventions that target adolescent's peer groups have been found to successfully decrease delinquency (Botvin & Griffin, 2004; Ellickson et al., 2000; Hansen & Dusenbury, 2004; Osgood et al., 2013a). Thus, identifying factors that promote resilience to peer influence is especially relevant for programs aimed at decreasing the criminal behavior of adolescents.

Third, when academics conduct research on resilience, they often choose to focus on external sources of resilience rather than internal, personal assets (Luthar, 2006). It is vital to consider internal assets in addition to and in conjunction with external protective factors. Internal assets may exert an independent influence and interact with external resources to encourage resilience amongst at-risk groups – for

example, internal processes can lead the individual to make external changes (Rutter, 2006). This process is especially important to our understanding of the reciprocal relationship of peer selection and influence (see Gallupe et al., 2019; Weerman, 2011). Agentic actors are not only influenced by their environment, but also influence their environment in turn (Paternoster & Pogarsky, 2009); specifically, individuals can select their own social influences by opting in and out of friendships. Good decision-making skills may then increase resilience to the environmental risk of deviant peers and lead adolescents to make important, impactful changes to their future environment. This again will have important implications for policy and practice, as improving adolescents' agency would encourage the selection of prosocial friends and decrease the power of delinquents in school networks (see Osgood et al., 2013b).

Fourth, the literature on deviant peer influence is under-reliant on rural samples. Researchers often study the impact of deviant peers using metropolitan-centered data sources such as the Project on Human Development in Chicago Neighborhoods (PHDCN; Zimmerman & Messner, 2011; Zimmerman & Vásquez, 2011) or the Pathways to Desistance Study of high-risk adolescents in the Philadelphia and Phoenix areas (Monahan et al., 2009; Steinberg & Monahan, 2007; Walters, 2016). Researchers also often make use of large, nationally representative samples including the National Youth Survey (Agnew, 1991; Warr, 1993) or the National Longitudinal Study of Adolescent Health (Add Health; Haynie & Osgood, 2005; McGloin, 2009). While nationally representative samples would include rural youth, there are few articles are specifically focused on this group. This gap extends

to work on susceptibility, vulnerability, or resistance to deviant peer influence, which is conceptually closest to resilience. For example, Gardner and colleagues (2008) study a metropolitan community with racial and ethnic diversity, Fergusson and colleagues (2007) study a small city in Quebec, and Goodnight and colleagues' (2006) sample is gleaned from Nashville, Knoxville, and Bloomington, Indiana.[1]

PROSPER Peers, conversely, is comprised of school districts in rural or semi-rural Pennsylvania and Iowa. Rural or semi-rural contexts differ dramatically from many other samples, and the processes of resilience and peer influence may be altered accordingly (Fergus & Zimmerman, 2005). For example, rural community members typically engage in more monitoring of adolescents and are aware of past misbehavior (Wuthnow, 2019). Rural communities have more strongly reinforced social norms against deviant behavior and social networks that exhibit more density and closure (Beggs, Haines, & Hurlbert, 1996; Marsden & Srivastava, 2012; Smith, 2003). This study can examine the relationship between decision-making skills and resilience to peer influence specifically among a rural and semi-rural population.

In chapter 2 of this dissertation, I review the literature on deviant peer influence and resilience, with a special focus on the potential role of thoughtfully reflective decision-making skills in promoting resilience directly and through the dissipation of deviant influences, and describe the research hypotheses. In chapter 3, I describe the data and measures used to operationalize these constructs – in this case, the PROSPER Peers dataset, a longitudinal data collection effort surveying a set of

[1] Notable exceptions include Botvin and colleague's (1998) study of substance use among middle-class rural geographic areas in New York State and Thomas and McGloin's (2013) use of Add Health, a nationally representative sample.

middle-school-aged students in Pennsylvania and Iowa from 6th to 11th grade. Additionally, I detail the methods and models I employ – including structural equation modeling with moderation and mediation techniques – to answer the research questions at hand. In chapter 4, I present descriptive information as well as the results of the structural equation models and sensitivity analyses. I find evidence that TRDM directly promotes resilience to deviant peer influence, especially amongst adolescents with a highly (but not entirely) deviant friend group, but do not find evidence of an indirect pathway whereby TRDM indirectly leads to resilience through prompting changes to the friend group. I conclude in chapter 5 with discussion of the study's implications and limitations and suggestions for future research.

CHAPTER 2: LITERATURE REVIEW

Having deviant friends is one of the strongest and most consistent predictors of adolescent delinquency (Pratt et al., 2010; Warr, 2002). Theoretical skeptics have long questioned whether self-selection into peer groups (i.e., one's own level of delinquency determining the friendships one chooses) could explain away the deviant peer effect (Glueck & Glueck, 1950; Gottfredson & Hirschi, 1990; Hirschi, 1969), spurring methodological advancements such as the use of longitudinal surveys (Elliott & Menard, 1996; Matsueda & Anderson, 1988; Thornberry et al., 1994), analytic controls for selection (Haynie & Osgood 2005; Osgood et al., 2013b; Ragan, 2016), and even experimental tests (Duncan et al., 2005; Gardner & Steinberg, 2005; Paternoster et al., 2013; Sacerdote, 2001) in an attempt to provide persuasive evidence regarding the peer influence effect. The product of such debates is a deviant peer effect now well-established across many samples, measurements, and methodologies (see McGloin & Thomas, 2019). As an example, Pratt and colleagues' (2010) meta-analysis of 133 studies found delinquent peers to have a significant effect, comparable to or greater than many other common correlates of criminal behavior and consistent across many methodological specifications. There are many ways whereby peers can influence adolescents' behavior (i.e. providing opportunities, co-offending, and group processes which alter the perceived risks and rewards of crime), but research on normative influence, or the transmission of delinquent definitions from one peer to another through a socialization process, dominates research and theory on the deviant peer effect.

Normative Influence of Deviant Peers

Early qualitative and correlational researchers noted that a delinquent individual likely had a host of delinquent peers or co-offenders, and that delinquent attitudes and strategies seemed to be transmitted from one delinquent youth to another (Breckinridge & Abbot, 1912; Shaw, 1930; Shaw & McKay, 1942). Ethnographers often described processes of learning and influence; for example, Sutherland (1937) captured the life of Chic Conwell, a professional thief who had learned to commit crime from deviant associates. Sutherland (1947) went on to theorize that crime, like any behavior, was learned. This was contrary to the multi-factorial etiological approaches common at the time, which argued that crime was the result of a variety of psychological and pathological problems and to which Sutherland himself had once subscribed (Sutherland, 1924). Sutherland was influenced by several other theoretical perspectives in addition to these early qualitative arguments. First, Sellin's (1938) and Wirth's (1931) work on culture conflict argued that society consisted of competing cultures, and thus competing systems of norms and values. As not everyone shares a set of prosocial values, individuals can culturally transmit attitudes favorable towards crime from one to another (Shaw & McKay, 1942). Second, symbolic interactionist perspectives construed behavior as shaped by the social world through the communication between others and the self. Specifically, the self is a product of shared meanings between oneself and others, where one's identity is

shaped by perceptions of how others view and react to him/her (Cooley, 1902; Mead, 1934).[2]

Sutherland's (1947) *Principles of Criminology* posited that criminal behavior is learned much like all other behavior. This learning includes techniques and skills integral to the commission of crime and the specific direction of motives, drives, rationalizations, and attitudes towards criminal behavior, referred to as definitions favorable or unfavorable to the law. According to Sutherland, the ratio of definitions favorable to unfavorable to law is what determines future behavior. The principle of differential association states if there are more definitions favorable to law breaking than definitions unfavorable to law breaking, that person is more likely to engage in crime – in this way, the character of one's associates has distinct bearing on one's own behavior. According to this perspective, exposure to any single individual that exhibits deviant behavior, accompanied by exposure to his or her definitions unfavorable to the law, will increase the likelihood of deviant behavior; yet, of particular interest is when deviant associations begin to *outweigh* non-deviant associations (i.e., the majority of one's social network exhibits deviant behavior). There should be little ambiguity about appropriate behavior when the social network is entirely deviant or non-deviant, and more ambiguity when the social network and its definitions are mixed. The definitions of one's associations also vary in strength and content according to their frequency (how often they are encountered), priority

[2] Symbolic interactionism is another mechanism through which normative influence is theorized to take place (Matsueda, 1988). If deviant peers comprise one's reference group, the generalized other through which one evaluates one's own identity, behavior, and potential appraisals will likewise be criminal. As appraisals of one's self through those around you (e.g., reflected appraisals) are linked to future behavior, this can encourage crime (Matsueda, 1992).

(whether the association was formed earlier in life), duration (length of the association), and intensity (whether they like and have a strong attachment with the association).

Sutherland stated that definitions are learned without clarifying *how* they are learned (Jeffery, 1965), although he did suggest he wished other theorists to elaborate (Sutherland & Cressey, 1960). It was these criticisms that led to the development of Burgess and Akers' (1966) differential reinforcement perspective and, later, Aker's (1973, 1998) social learning theory. Burgess and Akers expanded on Sutherland's principle of differential association with the goal of making the process of learning more explicit and incorporating key concepts from operant conditioning, a method of learning where behavior is modified through reinforcements and punishments. Operant conditioning was influenced by early psychological behaviorists – most notably Thorndike (1898), who stated that behavior will likely be repeated or ceased depending on its consequences (i.e. the law of effect), and Skinner (1938), who discovered he could alter animal behavior by providing positive or negative reinforcement in response to a desired action. Though human behavior is more complex than animal behavior, Skinner hypothesized that humans' future behavior is similarly determined by the consequences elicited from behavior, and thus will be altered by learning reinforcement contingencies over time.

Reinforcements are consequences that encourage the behavior, presenting a pleasing stimulus (positive reinforcement) or removing an aversive stimulus (negative reinforcement) in response to the behavior. Punishments discourage the behavior, either by presenting an aversive stimulus (positive punishment) or removing a

pleasant stimulus (negative punishment) in response to the behavior (Skinner, 1938). Behavior is likely to persist if it is reinforced more often than it is punished, and conversely more likely to desist if is punished more often than it is reinforced. For example, after receiving a positive reinforcement in the form of food, Skinner's pigeons learned pecking in that particular spot was likely to produce a reward and thus continued pecking. Key to Burgess and Aker's (1966) restatement of Sutherland's principles was the addition of these principles of differential reinforcement, or the balance of anticipated or actual rewards and punishments as consequences of the behavior.

Akers (1973) later expanded on this work, elaborating more fully into his social learning theory. This expansion was influenced by Bandura (1965), who studied vicarious learning through observing imitation/modeling in children. Bandura found that aggressive play in children with a toy called "the Bobo Doll" increased after watching adults playing aggressively with that same toy, emphasizing the importance of imitation of others, especially early behavior before reinforcement contingencies are established (Bandura et al., 1961). Aker's social learning theory thus included four elements, which reflected the influence of Sutherland, operant principles, and observational learning: 1) *definitions*, or one's attitudes on the acceptability, justifications, and neutralization towards criminal behavior (Cressey, 1955; Matsueda, 1988), 2) *differential association*, or an excess of definitions favorable versus unfavorable to crime, 3) *imitation*, or learning the modeled behavior of others via observation, and 4) *differential reinforcement*, or the anticipated consequences for a certain behavior.

The Importance of Peers During Adolescence

Scholars suggest normative influence from deviant peers is even more pronounced in adolescence due to increased exposure to peers, especially delinquent ones, and enhanced susceptibility to peers, including relative to other sources of influence. Adolescents are particularly likely to encounter deviant peer influences at this age (Brown et al., 1997; Warr, 1993; 2002), with more contact through shared institutions and a greater likelihood of having deviant friends. Youths spend a great deal of time with each other through institutions like school, sports, and other extracurricular activities (Payne & Cornwell, 2007). As the likelihood of encountering deviant others rises, so too does the likelihood of befriending them – for example, Haynie (2002) found that most adolescents (around age 15) had mixed delinquent and non-delinquent (56%) or entirely delinquent (28%) friend groups (see also Moffit, 1993).

During youth, individuals are also particularly vulnerable to peer influence. However, this does not imply that parents no longer exert an influence on adolescent development. Parents and peers exert separate influences on behavior (Barnes et al., 2006; Dishion & Loeber, 1985), and adolescents may prioritize one or the other based on the behavioral domain (Brittain, 1963; Warr, 2002). Parenting practices are also correlated with exposure to deviant peers (Elliott et al., 1985; Farrington, 1986). This relationship is intuitive; adolescents who are less attached to their parents and whose time is more laxly supervised have the most opportunity and motivation to socialize with deviant friends (Chung & Steinberg, 2006; Elliott et al., 1979, 1985). Conversely, the parents who more strictly monitor their children may not allow them

to engage with those they deem to be bad influences, and the children more strongly attached to a monitoring parent may avoid breaking their parents' rules (Warr, 2002). In this way, poor parenting practices can allow an adolescent to associate with deviant peers (see also Sutherland and Cressey, 1966).

Amongst the peers that adolescents encounter, adolescents do still tend to prioritize peers over other social referents, including parents, regarding deviant behavior (Brechwald & Prinstein, 2011; Walden et al., 2004). At this age, adolescents are forming an identity that is separate from their parents, and peers gain importance as adolescents hasten to establish their independence from family (Moffit, 1993). As this change takes place, peers become paramount and serve as vital social referents, taking the place previously occupied by familial ties (Moffit, 1993). Adolescents' concern with acceptance and belonging within their peer group grows, and they are acutely sensitive to gaining their peer's acceptance. Warr (2002) theorized that adolescents' fear of ridicule, enhanced sense of loyalty, and desire for status magnifies processes of normative influence from peers during this stage of life. Outside criminology, explanations are found in neuroscience. Research using MRI, fMRI, and other imaging techniques has found evidence that adolescents' brains are still developing, which may increase the salience of peer information received during this period (Blakemore & Choudhury, 2006; Grosbras et al., 2007) and the reward of risk-taking while observed by peers (Albert et al., 2013; Chein et al., 2011). Other explanations are found in studies of psychosocial development, as adolescents' identities are currently evolving and in flux (Collins & Steinberg, 2006).

Whatever the explanation, this research highlights the enhanced impact of friends, including delinquent influences (Monahan et al., 2009). This relationship varies across age and peaks in mid-adolescence. Berndt (1979) found that peer conformity in antisocial behavior was curvilinear, peaking at the 9th grade (around 14-15 years old), using a series of vignettes that tell the participants what their "best friends" would do before measuring behavioral intentions. An identical age trend was identified by Steinberg and Silverberg (1986) using the same measures. More recently, Gardner and Steinberg (2005) experimentally examined performance on risk-related measures across age groups, finding that adolescents (age 13 – 16) were more likely than older age groups to take risks in a computer game of "chicken" and report intention to commit other risky, antisocial behaviors while in a group setting compared to alone. Likewise, Steinberg and Monahan (2007) used data from four longitudinal and cross-sectional studies to find that across all groups, susceptibility to antisocial peer pressure (measured through self-reported scale of peer resistance) peaks at age 14 and decreases linearly through age 18. Through different forms of measurement and modeling, researchers consistently find adolescents aged around 13-16 to be most susceptible to the influence of deviant peers.

These research findings signal that many youths' capacity to resist (or display resilience to) peer influence is still developing during adolescence (Albert et al., 2013). This is consistent with criminology's field of normative influence, where theorists and researchers commonly extoll the strength of the impact of adolescent deviant peers. Since early research on peer influence, researchers have discussed deviant peers as if they represented a deterministic risk for adolescent delinquency –

for example, Breckinridge and Abbott (1912) once noted that that it was difficult to find a delinquent adolescent that was not accompanied by a delinquent peer group or influenced by delinquent companions, while Sutherland's suggestion that differential association theory could exemplify a theory "to which no exceptions can be found" highlights the deterministic thinking towards deviant peer influence (Sutherland et al., 1992, p. 86).

Although it could indeed be rare to find an adolescent that displays resilience to peer influence, it is not impossible. Presupposing adolescent's behavior based upon such retrospective observations is a logical fallacy – for example, Robins (1978) once noted that although most criminal adults were once delinquent children, most delinquent children did not become criminal adults. In a similar fashion, although most delinquent youth may be associated with deviant peers, a group of adolescents with deviant peers may avoid this common pitfall into delinquency. Although the existence of this group is implied by studies of adolescent resistance and susceptibility to deviant peers, it has not yet been formally identified or described. Identification of an adolescent group that displays resilience to deviant peer influence – and the factors that encourage this resilience – is all the more important, as finding ways to foster resilience to deviant peer influence across these ages could mitigate a great deal of antisocial behavior. Thus, the concept of resilience should be applied to the study of deviant peers.

Resilience

In the early 20th century, studies on war, poverty, psychopathy, and trauma dominated the field. Early psychologists concerned themselves with the impact of

risk, such as poverty, psychopathy, and trauma, on negative later-life outcomes, especially among children subject to extreme stressors (Garmezy, 1985; Rutter, 1985). Times of significant struggle, such as World War II or the Great Depression, placed seemingly insurmountable challenges in the paths of individual success. Theorists and practitioners expected notably bad disruptions to normal human development, especially among adolescents. Other research focused on more typical stressors, such as accidental deaths or injuries in the family or hereditary risks of schizophrenia and other psychopathologies. Yet, scholars soon noted that not all of those at risk were inextricably linked to such outcomes. For example, Norman Garmezy (1973) began his study of children at high risk for psychopathy (due to being the children of mentally ill parents) in the 40's and 50's. He and other psychologists, finding a similar subset of individuals that avoided the hypothesized negative outcomes (see Luthar, 2006; Masten, 2001), started the search for the "missing links" to explain why this group was protected from the maladaptive outcomes associated with significant risks; thus began the study of resilience.

Theoretical inspirations for the work of these scholars included Darwin's work on natural selection – while he stressed survival of the fittest, he also placed great emphasis on potential for adaptation in the face of challenges – and Freud's work on the human personality and the development of the ego, the decision-making component of the personality which can weigh the person's wants and external constraints in search of the best option (Masten & Coatsworth, 1995). Later, resilience found a theoretical foothold in the field of positive psychology, greatly influenced by Martin Seligman (see Seligman & Csikszentmihalyi, 2000). This field

focuses on the positive aspects of human nature that lead individuals to thrive, even in the face of challenges. Indeed, the distinguishing factor of research on resilience is its emphasis on individual variation in response to risks, acknowledging risk factors will not operate similarly for everyone (Rutter, 2006). The first wave of research focused on defining, identifying, and operationalizing resilience and its correlates, while the second wave explored the mechanisms and processes that promote these positive adaptations (Kolar, 2011; Liebenberg & Ungar, 2009; Masten & Obradović, 2006). The past few decades have seen a resurgence in academic interest in the study of resilience (Ungar, 2005), yet with little agreement among scholars on how to best define and measure resilience and the most fruitful future directions for study.

Resilience can be best described as positive adaptation in the face of adversity, such as experiencing trauma or psychosocial risk experiences (Luthar, 2006; Rutter, 1999; 2000). Specifically, this refers to the process of coping successfully with traumatic experiences, avoiding the negative trajectories associated with risks, or achieving good developmental outcomes despite these high-risk states (Fergus & Zimmerman, 2005; Werner, 1995). There are thus two distinct dimensions defining those who display resilience: 1) exposure to significant adversity and 2) positive adaptation (Luthar, 2006; Masten, 2011). In order to be considered a member of a "resilient" group, individuals must be at a high risk for a specific negative outcome, yet display positive (or at least a lack of negative) outcomes. Note that resilience research is not concerned with the lack of negative outcomes amongst those who were not particularly at a high risk of those outcomes, instead focusing on the disruption of high-risk trajectories. For example, adolescents with non-delinquent

friends who do not commit delinquency are not displaying resilience; they are acting in accordance with their risk factors, which are low.

Early on, person-focused models reigned, with researchers identifying "resilient" individuals to study their lives and compare with non-resilient groups. Later, variable-focused models were introduced to use multivariate analyses to study patterns, predictors, mediators, and moderators of resilience. This allowed for a more dynamic and shifting definition of resilience; indeed, it may be more accurate to describe overall resilience in "continuous rather than dichotomous terms" (Condly, 2006, p. 213) – meaning that though individuals may display evidence of resilience in one area (i.e. by avoiding crime), true "resilience" (defined as resilient in all contexts) is not likely and instead varies by degree. Defining an individual as "resilient" may thus be misleading, as many who demonstrate resilience in one area do not do so in all areas of life.[3] An individual can display resilience in one domain (such as academic competence) but not others (such as emotional adjustment); moreover, if an individual is "resilient" in one area but not others, problems resulting from those negative outcomes could spiral to disrupt the individual's resilience in the area of interest (such as an emotional breakdown leading to dropping out of school). These variable-focused models also allowed for more precise identification of the factors associated with increased resilience: protective or promotive factors.

The term "protective factor" was first used by Michael Rutter (1985), who demonstrated that protective factors interact with risk factors in order to mitigate the

[3] Though I do occasionally refer to adolescents as "resilient," I include quotation marks to demonstrate that this is short-hand signifying that this group of adolescents show signs of resilience in one particular domain: by avoiding crime in the face of deviant peer influence.

risk of some problematic outcome. This term was reserved for factors that had a special impact in the face of challenges. As more models of resilience emerged, so too did a distinction between "promotive" and "protective" factors (Sameroff, 2000). Promotive factors (also called compensatory factors; Fergus & Zimmerman, 2005; Zimmerman et al., 2013) hold universal positive effects, which may be so great as to eclipse the impact of the risk factors for those at the highest level of adversity. The impact of protective factors instead grows when the risk is at its highest to mitigate the impact of the risk factor. Although promotive factors have the same positive impact in both low and high risk groups, protective factors reduce or remove the risk at a greater rate for those at the highest level of risk (Sameroff et al., 2003). Many risk factors exist on a spectrum, where on one extreme the factor increases vulnerability and, on the other end, it is promotive or protective (Luthar, 2006). Yet, scholars stress that this is not necessarily the case; the inverse of factors that impact vulnerability do not necessarily make them promotive or protective factors, and the lack of promotive or protective factors does not necessarily put an individual at high risk. The challenge model identifies the level of the risk factor itself as impacting resilience, where low levels of the risk factor do not sufficiently equip individuals to learn to deal with the risk when it is eventually encountered, and high levels of the risk overwhelm individuals' coping skills and lead to maladaptive outcomes. According to this perspective, moderate exposure to a risk factor is said to be ideal, as it exposes individuals to a reasonable level of the risk to learn to cope and maintain resilience when encountering the risk in the future.

Initial inquiries into the nature of these protective/promotive factors started with a view of resilience as a purely individual (internal) phenomenon, then later expanded to include social and environmental factors. Promotive factors thus include both personal *assets* like competence, coping skills, self-efficacy, good decision-making skills and external *resources* like parental support, adult mentoring, social networks/capital, and community organizations (Fergus & Zimmerman, 2005). There has been a recent overemphasis on researching the latter, ignoring the more agentic personal assets for a focus on one's environment. As an example, Luthar (2006) stressed in her discussion of protective factors that "resilience rests, fundamentally, on relationships" (p. 780). This is in part driven by the identification of important external resources, but also by many resilience scholars moving away from research on personal assets because of the implication and the contention that they "overemphasize personal agency and neglect to consider structurally produced inequality and historical circumstance" (Kolar, 2011, p. 425). Although the importance of social and environmental resources should not be ignored, there is a need to understand the psychological and cognitive processes at play as well. Personal assets and environmental resources act in conjunction and interaction to promote resilience – for example, internal processes can lead the individual to make external changes, and environmental factors can facilitate the development of personal assets (Fergus & Zimmerman, 2005; Rutter, 2006). Although scholars disagree on the most fruitful future directions for the current wave of resilience research, most can agree that integration of research on internal and external

resources will improve our understanding of resilience (Liebenberg & Ungar, 2009; Masten & Obradović, 2006).

Specifically, the encouragement of personal assets can aid individuals in surmounting challenges and risk when external resources are insufficient. First, external factors still must be processed internally by the individual. Second, personal assets can independently explain resilience, and overlooking this possibility ignores the existence of adolescents who display resilience despite having no extraordinarily redemptive factors in their environment. Masten and Powell (2003) referred to this phenomenon, where individuals are often able to overcome significant risk factors using ordinary capabilities and resources, as "ordinary magic" (p. 15), which carries optimistic implications for human adaptation and interventions that facilitate the development of normal adaptive systems (Masten, 2001). Third, internal processes can lead the individual to make external changes (Rutter, 1987, 2006). External resources and individual assets thus operate together to promote resilience, and the adoption of one may promote exposure to or increased impact of another. Many interventions contemporaneously promote both assets and resources – for example, organized community efforts where adolescents are exposed to positive peers, role models, opportunities, and programming in a structured and controlled environment (Zimmerman et al., 2013).

This is not to suggest that adolescents who do not display resilience are to blame for their poor outcomes because they should have made better decisions – rather, it is an acknowledgment that these factors interact in order to promote resilience. Encouraging the development of personal characteristics likewise does not

require ignoring structural contributors to risk factor exposure and the development of personal assets. Influential factors can vary from genetics to quality of schools to familial and neighborhood environment, and studying how internal capabilities contribute to resilience need not blame adolescents for their lack of "invulnerability." Instead, a better understanding of the role of personal assets can inform researchers to what degree we can expect interventions aimed at increasing assets to succeed in fostering resilience amongst an at-risk group, which may be a great distance from isolation from the risk factors that surround them. Personal characteristics and socio-environmental characteristics likely act in interaction to promote resilience to deviant peers; the current study investigates one such interactional pathway. Both personal characteristics and socioenvironmental characteristics may be contributing factors to those who display resilience to risk factors that commonly encourage criminal behavior (Fergus & Zimmerman, 2005).

Resilience in Criminology

Resilience in criminology remains largely unexplored, but there are those that have suggested the importance of studying "negative cases" in regard to crime. For example, Reckless and colleagues (1957) outlined the theoretical importance of explaining the behavior of at-risk youths who avoided delinquency. Sullivan (2011) encouraged the examination of "deviant cases" – some of which display resilience to known predictors of crime – as necessary to understanding the full range of our data and driving our theoretical understanding and statistical modeling forward. Giordano (1989) analyzed negative cases to identify adolescents who should have been

delinquent, given their weak ties to parents, but were not, proposing the addition of new variables and modeling techniques based on her findings.

A few criminological pieces explicitly focus on resilience. McGloin and Widom (2001) matched adult interviews with prior cases of child abuse and neglect, establishing evidence of resilience among 22% of victims of abuse and neglect. The individuals who displayed resilience often avoided criminal behavior, such as substance use, arrest, and violence. A few longitudinal research pieces stemming from the Rochester Youth Development Study (RYDS) have identified groups at a high-risk for delinquent behavior that display evidence of resilience. For example, Smith and colleagues (1995) found about 60% of those with many risks for delinquency to be "resilient," with parent-child attachment, educational factors, prosocial peers, and self-esteem significantly distinguishing "resilient" youth from "non-resilient" youth. Later, Smith and colleagues (2013) also found the impact of maltreatment on criminal behavior to be weakly mitigated by educational factors. Using the Denver Youth Survey, Tiet, Hiuzinga, and Byrnes (2010) identified factors that promote resilience, defined as positive adjustment and avoidance of antisocial activities, for youths living in high-risk neighborhoods; impactful factors included prosocial bonds with family, teachers, involvement in extracurricular activities, and less involvement with delinquent peers.

Additionally, some avenues of research, although not explicitly focused on resilience, may shed some light on processes of resilience specific to criminal activity. First, control theorists have identified factors that inhibit rather than promote criminal behavior, such as attachments to family, school, and other prosocial

activities (Hirschi, 1969), high self-control (Gottfredson & Hirschi, 1990), and organized neighborhoods (Sampson & Raudenbush, 1999). These factors may not interact with risk, but represent additional forces in individual's lives that may possibly act as buffers against less constructive factors (i.e. promotive or compensatory factors). Scholars have indeed established various familial and environmental correlates impacting adolescent resilience that are common to control theories of crime, such as parental and religious attachment, participation in extra-curricular activities, educational achievement, educational and occupational aspirations/goals, and parental/adult monitoring (see Fergus & Zimmerman, 2005).

Second, Agnew's (1992) general strain theory asserts exposure to strains (similar to, but not identical to, the idea of a risk factor) leads to negative emotions, especially anger, which then motivates criminal behavior. Agnew posits that not all strained individuals will go on to commit crime, similar to the idea of resilience; it depends on how individuals adapt to these strains. Those exposed to strains can be "constrained" from committing crime due to external factors, such as social support, or internal factors, such as coping. In a similar vein to personal assets identified in resilience research, individuals can use developed cognitive, behavioral, and emotional coping strategies to positively adapt to strain and avoid the associated negative outcomes. Instead of coping *behaviorally* – which sometimes involves the commission of illicit acts to reduce negative emotions – coping *cognitively* will reduce the likelihood of crime (McGivern, 2010). Cognitive coping styles include redefining the situation and maximizing potential benefits, in line with TRDM skills.

Third, research on desistance, or offenders who later cease criminal activity, bears particular significance for studying resilience. Researchers in the broader field of resilience refer to desistance from negative outcomes as resilience through "bouncing back" (Rutter, 2006). Studies of criminal activity throughout the life course have found that the addition of such environmental and social control factors, such as a positive marriage and gainful employment, can act as "turning points" and disrupt criminal trajectories (Laub & Sampson, 1993; Sampson & Laub, 2003; Warr, 1993, 1998). Notably, these "turning points" resemble "turnaround points" identified in general resilience literature, including moving, joining the military, or a positive marriage (Rutter, 1990; Werner & Smith, 1992).

Other scholars have clarified that desistance may be preceded by or complemented by internal forms of change reflecting personal assets according to theories of resilience – for example, framing environmental shifts as "hooks for change" (Giordano et al., 2002), shifting identity to a more prosocial, redeemed version of oneself (Maruna, 2001; Paternoster & Bushway, 2009), or rational re-appraisal of costs and benefits of crime (Laub & Sampson, 2001; Sampson & Laub, 2003). These personal characteristics that promote desistance may act as protective factors and interact with risk factors in order to promote prosocial pathways. Moreover, they support the role of intentional action and choice in altering an at-risk group's likelihood of criminal behavior. These successful predictors of desistance may also predict the ability to avoid following in the footsteps of deviant peers and/or avoid their association and influence. For example, Giordano and colleagues (2004) found individuals who avoided recidivism had taken an active role in the deviant

composition of their friendship group, purposefully selecting out of friendships with deviant others and selecting into prosocial connections; this suggests intentional action and choice may be an important factor in promoting resilience to deviant peer influence.

Resilience to Deviant Peer Influence

Resilience to peer influence refers to those who refrain from criminal behavior despite exposure to deviant peers. Sutherland's contention that the conditions that cause crime "should always be absent when crime is absent" initially disallowed for the existence of a "resilient" group (Sutherland & Cressey, 1960, p. 74). Yet, with the relaxed approach of "soft behaviorism" found in later iterations of learning theory, researchers began acknowledging and striving to explain one's degree of vulnerability to learning deviant behavior from others (Akers, 1990). Although there are no direct studies of resilience to deviant peer influence (defined as the complete absence of deviant behavior in the face of deviant peer influence), studies identifying individual differences that decrease vulnerability/susceptibility and enhance resistance to peer influence can aid in the identification of promotive or protective factors. Those who display *resistance* to peer influence are less vulnerable to peer influence on average (reflected by a lesser estimate of the impact of peers) or have an enhanced ability (often self-reported) to resist peer pressure. Resistance to peer influence is thus conceptually similar to but distinct from resilience – it does not necessitate the complete avoidance of crime, but does require a lesser impact of deviant peers on the degree of antisocial behavior. The flip side of resistance to peer influence is enhanced *vulnerability* (or susceptibility) to peer influence, defined as the "the differential

tendency of individuals to be influenced by the attitudes, beliefs, and behaviors of their peers" (Meldrum et al., 2013, p. 106).

Research on resistance and vulnerability finds a number of correlates that may be relevant to the explanation of resilience to deviant peers. Information on gender differences is conflicting but trends towards the finding that males are slightly more susceptible to peer influences than are females (Steinberg & Monahan, 2007; Meldrum et al., 2013). As previously discussed, age alters the impact of peer influence over time, with young adolescents displaying the most vulnerability to deviant peer influence (Steinberg & Monahan, 2007). Peer processes themselves play a role; youth who place a high value on being a member of a group or social status and those who have low self-esteem are particularly vulnerable to the influence of peers, while it is unclear whether the number of reciprocated friendships impacts vulnerability (Aloise-Young et al., 1994; Urberg et al., 2003). Participation in extra-curricular or community activities, parental monitoring, family relationship quality, and parental support have also been found to compensate for deviant peer influence (see Fergus & Zimmerman, 2005).

Studies directly measuring the impact of decision-making skills with resilience or resistance to peer influence are rare. Yet, recent research has identified assets promotive of good decision-making that contribute to adolescent resistance/vulnerability or resilience to peer influence. This body of research has identified inconsistent effects, which may depend on which and in what way constructs are measured. Researchers have found levels of impulsivity, commonly assumed to decrease decision-making skills, to moderate the impact of deviant peers;

those with greater levels impulsivity or novelty seeking (respectively) are *less* susceptible to normative peer influence on delinquent behaviors (Fergusson et al., 2007; Thomas & McGloin, 2013).[4] The theoretical explanation offered for this finding is that that adolescents with low impulsivity are much more likely to factor in the behaviors and attitudes of their peers into their deliberations before choosing a course of action, causing increased susceptibility to deviance amongst these peers (Thomas & McGloin, 2013).

Conversely, low levels of reward dominance and high levels of self-regulation have been found to decrease risk of later delinquency in the face of deviant peer influence (Gardner et al., 2008; Goodnight et al., 2006). Reward dominance refers to greater sensitivity to rewards than to punishments; those with low reward dominance can interrupt reward-oriented behavior in the face of threats of punishment (Goodnight et al., 2006). Self-regulation includes goal setting, planning, task persistence, and behavioral, emotional, and attentional control. Those with high levels of self-regulation can resist immediate rewards when they threaten long term outcomes, including the rewards offered by one's deviant peer groups. The authors found that the ability to use effortful control and resist the pull towards the rewards provided by one's deviant peer group contributed to behavioral resilience (Gardner et al., 2008). Additionally, Botvin and colleagues (1998) found strong decision-making skills, measured with a scale not unlike TRDM (Wills, 1986), to not only compensate for but also *reverse* the direction of the deviant peer effect.[5] Among adolescents with

[4] Meldrum, Miller, and Flexon (2013) also discussed the role of impulsivity in susceptibility to deviant peer influence; however, the study did not directly measure the presence of deviant peers.
[5] Despite some similarities to Botvin and colleague's (1998) study, my dissertation differs from this study in a few key ways. First, I focus on forms of delinquency rather than adolescent substance use,

good decision-making skills, there was a significant negative relationship between peer marijuana usage and adolescent's own drinking behaviors, compared to a significant positive relationship for adolescents with poor decision-making skills. The authors interpreted this to mean good decision-making skills were protective against exposure to peers who drank alcohol, and that more programs stressing decision-making skills will aid in preventing adolescent drinking behaviors. Given the inconsistent evidence, more research is warranted; tentatively, I hypothesize TRDM will operate differently from low impulsivity/ high self-control (i.e. Thomas & McGloin, 2013) and instead increase the likelihood of adolescents displaying resilience to deviant peer influence.

Decision-Making Skills

Decision-making research in the study of crime can be traced back to the philosophies of Cesare Beccaria (1738-1794) and Jeremy Bentham (1748-1832). Beccaria, often identified as the father of deterrence theory, acknowledged the role of choice in criminal behavior by suggesting that individuals can be deterred from criminal behavior by swift, severe, and certain punishments. Beccaria wrote *On Crimes and Punishments* during the Enlightenment in response to the draconian practices of the criminal justice system at the time. Crime was often seen as rooted in

---

which arguably would have more serious, long-lasting consequences. Second, I focus explicitly on resilience to deviant peers – the complete avoidance of these delinquent acts – rather than enhanced/decreased vulnerability of adolescents to deviant peers based on decision-making quality. In doing so, I remove from my sample adolescents who were not exposed to deviant peers in the past year. Third, while Botvin and colleagues (1998) split the sample by level of decision-making style to examine moderation, I examine the interaction of decision-making and deviant peer influence by the multiplicative score of two continuous measures and by a multigroup analyses separating the sample by level of deviant peer influence. The latter analysis will examine whether TRDM is – linearly or nonlinearly – increasingly protective at higher levels of risk, to which Botvin and colleagues' (1998) analysis cannot speak.

spiritual forces, using brutal punishments to rid the body of evil or demonic possession. Beccaria posited that humans are rational beings and crime can be deterred through sanctions that are swift, certain, and severe. In this way, crime can be prevented rather than simply punished. Bentham (1789) likewise departed from deterministic schools of thought common in that day by stating that potential courses of action can lead to either pleasure or pain and individuals will follow the course of action that holds the greatest utility.

There was a resurgence of academic focus on deterrence theory and later, rational choice theory, beginning in the mid-20th century. This intellectual curiosity regarding decision-making research was largely brought on by Gary Becker's (1968) article "Crime and Punishment: An Economic Approach," which illustrated the usefulness of the expected utility model for understanding criminal behavior. Over 200 years later, Becker's model brought back the "hedonistic calculus" posited by Bentham – individuals will judge their future action based on which action had the greatest utility (the most pleasure and the avoidance of pain). Much like Bentham, Becker acknowledged that rational actors would be expected to act in ways that would maximize their benefits and minimize costs, insomuch that they would be expected to act if the benefits outweighed the amount and likelihood of experiencing the costs:

$$U(benefits) > pU(costs)$$

Rational choice theory of criminal behavior posits that individuals decide whether or not to commit crime much like the way they decide to engage in non-criminal behaviors: by engaging in a rational decision-making process (McCarthy, 2002;

Paternoster & Pogarsky, 2009). Later, Clarke and Cornish (1985) echoed the ideas that offenders commit crime due to the balance of rewards and punishments likely to occur as a result of that action.

Decision-making researchers first underwent macro-level tests of deterrence, using aggregate data to study the impact of the death penalty and incarceration on crime rates (Gibbs, 1968; Tittle, 1969), then moved on to study individual perceptions of punishment threats longitudinally (Paternoster et al., 1983; Saltzman et al., 1982). These methodological changes led to many theoretical revisions. Most notably, Stafford and Warr (1993) did not just measure the impact of punishment, but also punishment avoidance, and did not just include individuals' personal experiences, but also their vicarious observations. Other researchers noted that it is not just legal costs and rewards that matter, but also extralegal factors, such as social rewards and punishments (Clarke & Cornish, 1985; Williams & Hawkins, 1986). These ideas were consistent with the ideas of social learning theory, including differential reinforcement and reinforcement contingencies (Akers, 1996).[6] Thus, the two separate fields of deterrence and rational choice began to merge to focus on the broader perspective of individual decision-making, including the role of social factors.

Individual decision-making is now an interdisciplinary, broad field linked by its focus on examining individuals' rational decision-making processes. For example,

[6] Akers (1990) argued that rational choice theory is essentially equivalent to social learning theory. According to principles of operant conditioning, both legal and informal sanctions act as punishments, while the rewards of crime reinforce the behavior. The inclusion of moral beliefs, including moral rewards and punishments associated with engaging in crime, served to further rational choice theory's connection with the principles of normative influence. As social learning theory only represents a form of "soft behaviorism," it too allows for cognitive processes of deliberation before choosing an action.

economics researchers developed theories on the expected utility of actions (von Neumann & Morgenstern, 1947) and rational choice (Becker, 1968), assuming that individuals have preferences and individuals will act in accordance with these preferences to maximize their subjective expected utility. Psychology researchers studied the cognitive processes involved in the selection of a course of actions from two or more alternatives, including judgment, reasoning, and problem-solving skills, and individual's ability to make accurate judgments (Baron, 2004; Byrnes, 2002; Rescher, 2003). Behavioral economics has emerged out of the junction of psychology and economics to explain actors' systematic departures from the most rational option (see Kahneman, 2011; Thaler & Sustein, 2008; Tversky & Kahneman, 1974).

Departures from Rationality

Most persons, indeed, are not perfectly rational, and there are differences both within and between persons in the ability to undergo a rational decision-making process (Loewenstein, 1996; McCarthy, 2002; Simon, 1957; Thaler & Sustein, 2008). Simon (1957) first introduced the concept of bounded rationality, which acknowledges all are subject to factors that limit our capacity to make entirely rational decisions. Our decision-making can suffer from time and information constraints, heuristics and biases, emotional processing, and other factors that encourage irrational choice-making. Acknowledging these limitations, rational choice then refers to engaging in a rational decision-making *process* rather than arriving at a perfectly rational *outcome*. While the expected utility model describes how humans should choose actions, behavioral economics describes how humans make behavioral choices in practice (Thaler, 2015). Human decision-making tends to depart from

rationality in systematic ways – both within-person, given shifting contexts, and between-persons, given individual differences. This body of research can help us explain why individuals choose to commit crimes, a decision fraught with uncertainty that most find irrational in the long-term (Paternoster et al., 2011).[7]

Within-person variation in criminal decision-making acknowledges that there exists certain contexts or circumstances under which individuals systematically depart from rationality. For example, individuals may depart from rational decision-making styles under certain contexts that involve ambiguity (Loughran et al., 2011), the choice framed as a loss (Tversky & Kahneman, 1981), or the influence of emotional or social factors (Van Gelder, 2013). Kahneman (2011), in *Thinking, Fast and Slow,* laid out a dual-process theory of decision-making processes; System 1 involves intuitive, automatic, and immediate thought processes, more prone to reliance on heuristics and biases that increase the likelihood of irrational choices, while System 2 invokes slow, reasoned, and conscious thought. Many crimes are unplanned, impulsive, and take place in groups – contexts wherein individuals are likely to rely on System 1 decision-making. Another source of within-person variation is age. Adolescence is known to be a time during which a person's decision-making skills suffer. Adolescents are specifically vulnerable to making risky decisions and overemphasizing rewards, particularly in the presence of peers (Gardner & Steinberg,

[7] Rational choice assumes that individuals act in accordance with their preferences and in their best interest; in assuming that the rational choice is for individuals to avoid crime, we also assume that individuals do not have a preference for crime or that crime doesn't provide long-term benefits beyond those offered by conventional activities. It stands to reason that this is true for most, but not all – specifically, those who are greatly oppressed or under a great deal of economic duress may *rationally* decide to engage in crime (see Laub & Sampson, 1993). As Paternoster and colleagues (2011) explain: "For a few, crime is rational, for others, crime is irrational…" (p. 10).

2005; O'Brien et al., 2011). Decision-making improves with age, alongside cognitive developments (Mann et al., 1989; Steinberg & Cauffman, 1996).

Yet, even in adolescence, there are *between-person differences* in the tendency to use undergo rational decision-making processes. Researchers have identified differences in decision-making according to impulsivity/self-control or present orientation, finding those who are more impulsive or present-oriented to value immediate rewards over risks (Mamayek et al., 2017; Nagin & Paternoster, 1993, 1994; Nagin & Pogarsky, 2001, 2004). Dual-process models and thoughtfully-reflective decision-making further elaborate on between-person differences in decision-making skills: whereas some individuals rely on impulsive, intuitive thinking (i.e. System 1), others may be systematically more likely to engage in effortful, slow thinking (i.e. System 2) to make important decisions (Kahneman, 2003, 2011). Similarly, Paternoster and Pogarsky (2009) acknowledge that not all persons are equally skilled at decision-making, with some engaging in more thoughtful processes than others.

Thoughtfully Reflective Decision-Making

Paternoster and Pogarsky's (2009) conceptualization *of thoughtfully-reflective decision-making* (TRDM) refers to a person's tendency to undergo a slow, thoughtful, deliberative, careful, reasoned, and reflective decision-making process. Individuals who engage in TRDM 1) gather information relevant to a decision at hand, 2) identify the potential courses of action, including comparing the costs and benefits of these alternatives, 3) systematically reason over the alternative possibilities, making a decision based on this consideration, 4) and, after making a choice, reflecting back

upon the decision-making process and the outcome to analyze the quality of one's problem solving. Engaging in TRDM thus involves the slow, deliberate processes similar to the System 2 described by Kahneman (2003, 2011). Consistent with rational choice theory, TRDM also refers to undergoing a process that involves deliberation and consideration of one's past experiences in making future decisions (see Anwar & Loughran, 2011; Lochner, 2007; Matsueda et al., 2006; Paternoster et al., 1983). Theoretically, TRDM should aid individuals in discriminating between choices to identify the best options, leading to better short- and long-term outcomes. By engaging in a "good" process, reducing the chance of acting in a biased manner, the individual should come to a "good" decision, which will make "good" life outcomes more likely. Indeed, individuals who make thoughtfully-reflective decisions are more likely to experience positive outcomes, including avoiding delinquency/risk behaviors and increasing college attendance (Paternoster & Pogarsky, 2009).

TRDM acknowledges several forms of variation in decision-making. In the view of Paternoster and Pogarsky (2009), TRDM is an attribute that varies over time, maturing with age or in response to learning better decision-making skills (see Thaler & Sustein, 2008). Importantly, TRDM also varies between-persons, dependent upon multidimensional factors affecting personal competency, including the individual's personality, maturity, intelligence, executive functioning, motivation, emotional regulation, and socio-structural characteristics (Paternoster & Pogarsky, 2009). Thus, individuals have different levels of decision-making skills that go on to influence their level of short- and long-term success, including ability to avoid criminal behavior.

Paternoster and Pogarsky (2009) first demonstrated the validity of this concept by finding support for the operationalization of TRDM, including its theoretical and empirical distinction (using factor analysis) from the related concept of self-control. Second, using data from the National Longitudinal Study of Adolescent Health (Add Health), they demonstrated that TRDM is positively associated with prosocial outcomes and negatively associated with antisocial outcomes; engaging in a slow, reasoned decision-making process increased adolescents' likelihood of refraining from criminal and risky behaviors, graduating from college, and engaging in community and civic participation in later years (Paternoster & Pogarsky, 2009; see also Paternoster et al., 2011).

Focusing on the actor's decision-making skills acknowledges the actor's personal agency, or acting with intention. This is consistent with research and theory in the area of rational choice, which emphasizes the role of choice in human behavior (McCarthy, 2002; Nagin, 2007). The authors define agency as similar to rationality, stating "if rationality is making choices consistent with preferences, then agency is intentionally doing things in the world to make that consistency come about," (Paternoster & Pogarsky, 2009, p. 111). Agency is thus the action-oriented analog of the cognitive concept of rationality. Individuals act with agency by weighing the costs and benefits, prioritizing the features of the decision that they view as most important, engaging in choice-making, acting in ways consistent with their behavioral intentions, and reflecting back upon the success of their decision-making process (Bandura, 2001; Becker, 1968; Cornish & Clarke, 1986; Paternoster & Pogarsky, 2009). Paternoster and Pogarsky (2009) thus argue that TRDM is a good operationalization

of agency, stating that it will lead to "good choices… consistent with preferences" (p. 113). The decision that actors using TRDM come to should be the one most consistent with their long-term preferences or goals (Paternoster et al., 2011).

Paternoster and colleagues (2009, 2011) argue that TRDM is a better way of making decisions than the alternative; for example, Paternoster and colleagues (2011) state that "thoughtfully reflective decision making is an effective 'discrimination ability' by which one selects the most likely behaviors that will produce favored outcomes" (p. 2) and that "in the long run one's decisions will lead on average to more successful outcomes than those made on the basis of intuition or any other means" (p. 6). It is not just about the decision-making process, although the process is certainly important – the decision that one makes using TRDM should be competent and correct (Byrnes, 2002). Paternoster and colleagues (2009, 2011) posit (and find evidence) that TRDM should be accompanied by long-term personal success.

TRDM and Resilience to Deviant Peer Influence

As previously discussed, prior research on constructs related to decision-making presented mixed evidence on whether these constructs enhanced or lessened vulnerability to deviant peer influence. Particularly, studies found that adolescents with more deviant peers had an increased likelihood of deviance if they had low impulsivity (Thomas & McGloin, 2013) or novelty seeking, which is conceptually close to the ways impulsivity and self-control are discussed in criminology. (Fergusson et al., 2007).[8] Thus, I focus my discussion here on why I would expect

[8] Specifically, Fergusson and colleagues (2007) measured novelty seeking with a teacher-reported 11-item scale designed to assess "hyperactive, impulsive, and novelty-seeking behaviours" (p. 38).

TRDM to moderate the influence of deviant peers in a way that differs from constructs like impulsivity and self-control.

I hypothesize TRDM will operate differently from low impulsivity and self-control (i.e. Thomas & McGloin, 2013) and instead be protective under deviant peer exposure for three reasons. First, though related to one another, the decision-making concepts included in these studies remain distinct constructs and impact on behavior will thus vary. Particularly, the concepts which have been found to heighten vulnerability to deviant peer influence are empirically and conceptually distinct concepts from TRDM (see Paternoster & Pogarsky, 2009). Second, TRDM is hypothesized to not only alter the decision-making *process*, but also influence the quality of *outcomes*. That is, those with high levels of TRDM are theorized to be able to resist the pull of risk factors towards behaviors that would lead to less positive outcomes over time. Third, as these concepts are theoretically distinct, they tend to be measured in different ways in prior research.

The discussion of both impulsivity and self-control has its criminological roots in Gottfredson and Hirschi's (1990) general theory of crime. Self-control, as defined by Gottfredson and Hirschi (1990), is a unidimensional construct representing "the differential tendency of people to avoid criminal acts whatever the circumstances in which they find themselves" and "the idea that people also differ in the extent to which they are vulnerable to the temptations of the moment" (p. 87). This construct was hypothesized to be a unidimensional construct made up of different elements, including preference for easy or simple tasks, preference for physical over mental tasks, self-centeredness, volatile temper, a tendency towards risky and exciting

behaviors (risk-seeking), and a preference for immediate gratification (impulsivity) over things that might have long-term benefits (Gottfredson & Hirschi, 1990; Grasmisk et al., 1993). Its definition has since been subject to revision[9] and the unidimensionality of self-control questioned – with researchers particularly finding large and independent effects for impulsivity and risk-seeking (Arneklev et al., 1999; Burt et al., 2014). The consistent thread running through the conceptualizations and operationalizations of self-control is an orientation or preference towards the here and now, similar in nature to impulsivity. Thus, impulsivity is an important part of self-control, but the two constructs are not identical.

Paternoster and Pogarsky (2009) describe TRDM as empirically and conceptually distinct from self-control, with measures most conceptually similar to impulsivity. TRDM involves the use of one's cognitive facilities to weigh alternative options and reflect back on one's decisions. The main conceptual difference lies in the focus on the "here and now," or immediate gratification. As Gottfredson and Hirschi (2019) describe, "actors differ in the significance they place on the long-term costs of criminal behavior" (p. 7). Those with low self-control or high impulsivity will thus see immediate benefits as inherently more rewarding.

Importantly, the inverse of making thoughtful, reflective decisions does not necessitate acting on an impulse or with a preference for risk or immediate

[9] Hirschi and Gottfredson (1994) redefined self-control as the tendency to avoid acts whose long-term costs exceed the momentary benefits, and Hirschi (2004) later referred to it as the tendency to consider the full range of costs of a potential act. Most recently, Gottfredson and Hirschi (2019) defined self-control as "the tendency to forgo acts that provide immediate or near-term pleasures, but that also have negative consequences for the actor, and as the tendency to act in favor of long-term interests" (p. 4). Though these definitions of the construct continue to inch closer to TRDM, they are still couched in the ability to resist the draw of the immediate environment.

gratification, as impulsivity or the lack of self-control are often defined. One can undergo a thoughtful decision-making process, but still be unable to resist the urge of immediate gratification (i.e., see the immediate gratification as so rewarding that it outweighs the long-term costs). Likewise, one can refrain from undergoing an especially thoughtful and reflective decision-making process, but still resist the temptations of immediate gratification in the moment. While engaging in TRDM may make it more likely that an adolescent is able to resist the urge to act impulsively in that instant, it will not necessarily cause an impulsive individual to determine that the rewards of the immediate moment do not outweigh the risks to the future. However, TRDM's positive impact should still be observed in models that control for self-control or impulsivity of individuals.

A second theoretically-based argument for a prosocial impact of TRDM on deviant peer influence processes is whether the construct alters only the decision-making *process* or whether it should also influence the quality of *outcomes*. Some decision-making constructs, such as the dual systems approach, do not make assumptions about the prosocial or antisocial nature of the decision being made (see Kahneman, 2011, discussed in more detail later). For instance, if a person comes across a wallet on an empty street, an impulsive, system 1 response could include the decision to pick it up and put it in your own pocket or, conversely, yelling after the person you think may have dropped it. Likewise, after undergoing thoughtful, system 2 deliberation, you may decide in favor of either behavior. In other words, decisions with prosocial outcomes can stem from either system.

TRDM does not make the same assumption of neutrality. Paternoster and colleagues (2009, 2011) argued that TRDM is a better way of making decisions than the alternative; for example, they state that "thoughtfully reflective decision making is an effective 'discrimination ability' by which one selects the most likely behaviors that will produce [favorable] outcomes" (Paternoster et al., 2011, p. 2). It is not just about the decision-making process – the decision that one makes using TRDM should be competent and correct (Byrnes, 2002). Paternoster and colleagues (2009, 2011) posited (and found evidence) that TRDM should be accompanied by long-term personal success. If this holds true, decision-making skills in the spirit of TRDM should decrease susceptibility to peer influence and fit nicely into discussions of resilience as an example of a protective personal asset.

Third, as these concepts differ theoretically, so too does their measurement. Gottfredson and Hirschi typically recommended measuring self-control as a scale of either other negative behaviors indicative of low self-control or of inhibiting factors that would ostensibly prevent delinquency amongst an individual with high self-control. For example, Hirschi's (2004) operationalization of self-control included things such as not liking school, not doing homework, and being emotionally distant from parents. However, much of the field has measured self-control and impulsivity with scale items that ask more direct questions about an individual's orientation towards the present and ability to delay gratification. For example, Grasmick and colleague's (1993) operationalization of impulsivity included prioritization of what brings "pleasure here and now, even at the cost of some distant goal" and more concern with "what happens to me in the short-run than in the long run" (p. 14-15).

Thus, both old and new conceptualizations of self-control have traditionally been measured in ways distinct from TRDM. Whereas TRDM focuses more on decision-making styles, measures of self-control and impulsivity tend to ask questions that represent one's preference for immediate gratification. A typical measure of self-control or impulsivity, generally going with a "gut feeling" rather than thinking too much about the consequences of each alternative, has accordingly been found to be empirically distinct from TRDM in factor analyses (Paternoster & Pogarksy, 2009).

Overall, the evidence supports the contention that TRDM lessens the impact of deviant peer influence and that TRDM should maintain a positive effect under a high level of deviant peer exposure. TRDM is defined as not just undergoing a rational process, but also coming to a rational outcome (Paternoster & Pogarsky, 2009). In prior research, it seems as the conceptual measurement gets further from impulsivity and approaches decision-making styles, the concept's likelihood of demonstrating protective effects increases. TRDM is conceptually and empirically different from impulsivity and novelty seeking (close in its conceptualization to impulsivity and self-control) which have been found to lessen sensitivity to normative peer influence (Fergusson et al., 2007; Thomas & McGloin, 2013). TRDM more closely resembles the concepts that decrease susceptibility to peer influence – such as goal-setting, planning, and decision-making skills – and should be measured and modeled accordingly. Yet, the existing studies in this area have not examined the role of decision-making skills in resilience to peer influence. The existing studies do not 1) isolate the sample to those exposed to the risk factor or 2) focus on the absence of delinquency as an outcome measure. In this study, I examine decision-making skills

specifically through the lens of TRDM and its role in the avoidance of delinquency in the face of deviant peer influence.

Individuals with high TRDM supposedly stand capable of disrupting the irrational decision-making processes; the presence of deviant peers is one such context which can beget choices which may be rewarding in the short-term, but irrational regarding long-term success (Gardner & Steinberg, 2005; O'Brien et al., 2011). According to theorizing on TRDM, it is this tendency to consider the long-term life outcomes that can disrupt criminogenic peer processes. When exposed to deviant peers, individuals who exhibit TRDM may opt to analyze the situation, interpret the deviant peer influence through the lens of long-term success, and opt to maximize future benefits and minimize future costs, similar to the cognitive coping styles discussed within Agnew's (1992) general strain theory.

Good decision-making skills can directly impact resilience to peer influence and better life outcomes by increasing the likelihood that adolescents resist the urge to act impulsively or with a preference for risk or reward in the presence of peers and include information beyond peers in the decision-making process (Gardner et al., 2004; Goodnight et al., 2006). This increases the likelihood of adolescents with TRDM selecting prosocial behaviors that will have positive consequences in the short-term and in the distance future. If this is true, TRDM will have a direct, positive relationship with avoiding delinquency. Yet another way that TRDM may be linked with positive outcomes is through actors shaping their environment using positive decision-making skills.

Prosocial Capital

As Paternoster and Pogarsky (2009) explained, "[Agentic actors] do not, therefore simply respond to the roles and institutions they are involved in, but create those roles and institutions, thereby enforcing their will" (p. 105). Those who utilize TRDM may play an active role in their environment by accumulating prosocial forms of capital. Indeed, Paternoster and colleagues (2009, 2011) posited TRDM would also have an *indirect* impact on later-life outcomes, stating that "those who generally make good decisions are more likely to see opportunities, investments, and resources in their lives and as a result will accumulate greater human, social and cultural capital… and those with greater capital will be less likely to commit crimes and be conventionally successful" (p. 110-11). Opting into prosocial relationships likely involves ridding themselves of the negative influences in favor of more prosocial networks overall (Giordano et al., 2004). Good decision-making skills can thus have an *indirect* impact on avoiding delinquency in the face of deviant peers through actors selecting out of criminal relationships and into prosocial forms of capital.

In support of this hypothesis, Paternoster and colleagues (2009, 2011) analyzed Add Health data, finding that the relationships between TRDM and college achievement, illegal drug use, and civic and community engagement were partially mediated by the accrual of human, cultural, and social capital. Developing prosocial forms of capital was linked to one's decision making skills; the adolescents who made thoughtfully reflective decisions were more likely to accrue human (higher grade point average), cultural (engaging in hobbies and attending events), and social (school and primary caretaker attachment) capital (Paternoster et al., 2011). While

there was still a direct impact of TRDM on positive later-life outcomes, TRDM did prompt adolescents to select into more positive forms of social and cultural capital that explained part of TRDM's overall impact on these outcomes.

Paternoster and colleagues (2011) explain why persons would select into certain forms of capital. According to the theorists, those who engage in TRDM are more likely to take deliberative steps to shape their social environments and make investments in forms of capital that will later beget personal success. In this way, TRDM increases the likelihood of forming prosocial connections and attachments; this will strengthen the relationship between TRDM and prosocial behaviors as the investments in positive social connections are associated with prosocial behaviors, as well. This is consistent with research in resilience suggesting personal assets and environmental resources are linked. Those with good decision-making skills are more likely to identify opportunities and potential resources in their environment, thus opting into more forms of human, cultural, and social capital (Coleman, 1988).

Coleman (1988) and Bourdieu (1980, 1986), though not the first to use the term, are often attributed with identifying the importance of social capital as the social analog of physical capital (tangible, physical resources that aid success). Social capital acknowledges that one's relationships also represent a form of resource, focusing on the structure of the social networks, the trust and reciprocity between network members, and the ways in which networks can facilitate actions of the actors within its structures (Coleman, 1988; Putnam, 2001). Those with a high degree of social capital have many relationships, both familial and extra-familial, that help actors pursue their goals (Coleman, 1994). For example, social relationships serve as

information channels, communicate normative behavior, and lead to other forms of opportunity (Putnam, 2000). Social capital can beget other forms of capital, such as human capital, one's skills and capabilities relevant to participation in the labor market (Becker, 1964), or cultural capital, "interest in and experience with prestigious cultural resources" (DiMaggio & Mohr, 1985, p. 1233) that signals social mobility and status (Bourdieu, 1986).

The idea of social capital is consistent with that of agentic, deliberate actors. People often purposefully pursue and form relationships, maintaining relationships that benefit themselves and letting go of those that do not (Coleman, 1988; Lin, 2002). However, social capital is neutral in regards to the value of the behavior facilitated by one's networks (Coleman, 1988; Hagan & McCarthy, 1997; Putnam, 1995) – just as social connections with individuals in the labor market can increase employment opportunities, criminal ties can foster criminal opportunities (see discussions of criminal capital; Loughran et al., 2013; McCarthy & Hagan, 1995). Thus, in order for social capital to become *pro*social capital, one's networks must be comprised of prosocial others.

Prosocial forms of social capital are consistently linked to positive life outcomes. Social capital can lead to increased educational, occupational, and income attainment (Baron & Markman, 2003; Coleman, 1988; Furstenberg & Hughes, 1995). For example, Furstenberg and Hughes (1995) used longitudinal data to find social capital to be positively associated with educational attainment, labor force participation, and avoiding criminal behavior (see also Brehm & Rahn, 1997; Hagan et al., 1996; Smith et al., 1995). Social capital is often attributed with protective

qualities; for example, its aggregated analog, collective efficacy, is found to protect high-risk neighborhoods from poor outcomes (Sampson et al., 1999). Children with high levels of conventional human, cultural, or social capital may thus display resilience when it comes to risk (Coleman, 1988; Sameroff et al., 2003).

Social capital can be familial or extra-familial (connections to formal or informal persons or institutions; Coleman, 1988). Adolescent's peers represent one form of extra-familial social capital. As previously established, adolescence is a time of enhanced peer influence, given the frequency of interactions, desire for independence, and sensitivity to acceptance (or ridicule) by one's peers (Moffit, 1993; Stenberg & Monahan, 2007; Warr, 2002). Peers then represent a particularly important context for adolescents to accrue prosocial, extra-familial capital. That is, adolescents who *select into* prosocial friendships may especially benefit from their influence during this time of enhanced vulnerability to peers.

Peer Selection

Individuals generally tend to have friends that are similar to themselves; homophily and homogeneity refer respectively to the tendency for friends and peer groups to resemble one another (Cohen, 1977; Kandel, 1978). Initially, learning theorists such as Sutherland and Akers stressed processes of socialization (through normative influence) over peer selection – that is, that adolescents' behaviors were similar to their friends because of the influence those friends exerted, not because they chose friends similar to themselves (Akers, 1973; Sutherland, 1947). This was followed by researchers that questioned whether peer influence takes place at all, attributing similarity in behaviors only to selecting friends similar to oneself (Glueck

& Glueck, 1950; Hirschi, 1969). The product of this theoretical debate was a body of evidence demonstrating that these two processes are not mutually exclusive and have complementary and reciprocal effects on adolescent behavior (Elliot et al., 1985; Elliott & Mernard, 1996; Thornberry, 1987).

Influence occurs not only through a process of socialization, but also through a process of selection (Kandel, 1978). Adolescents' traits and behaviors impact the friends that they select, then adolescents' behaviors and traits are influenced by the friends they have selected, and so on and so forth. New approaches to studying peer homophily and homogeneity, including advances in analytical methods, focus instead on the joint processes at work. Network researchers find support that adolescents both select peers based on behavioral similarity *and* are influenced by these peers during adolescence (Gallupe et al., 2019; Osgood et al., 2013b, 2015; Ragan, 2020). Some researchers have suggested that peer selection and influence unfold over a multi-stage process, where selection may be most important in early years when adolescents are beginning to initiate antisocial behavior; selection provides the social context, and then processes of influence come into play as the social context reinforces the antisocial behavior (Leung et al., 2014; Urberg et al., 2003). Although there are some differences in research findings on age and the importance of peer selection, there is overall support for processes of selection into deviant peer groups in early-to-mid adolescence, with selection effects identified as early as 10 and extending to around age 16 (Burk et al., 2012; Mercken et al., 2012).

Discussion of peer selection is consistent with the ideas of rational actors choosing connections that beget a desired form of social capital. Yet, studies of peer

selection over time often neglect the ability of choice to disrupt these reinforcing processes, as adolescents who decide to make behavioral changes may select into different social contexts. As Haynie (2002) describes: "Individuals select friends who have similar behavior to themselves, once the friendship is formed influence occurs which increases similarity, and individuals select out of networks when their behaviors no longer coincide with the group's behavior" (p. 127). Thus, a change in behavior can be instigated by a change in the friends one selects rather than a change in the degree of peer influence; moreover, there is the potential for the largest influence amongst those who have significantly changed their social contexts (Urberg et al., 2003). Coleman (1994) describes social capital as "created when the relations among persons *change* in ways that facilitate action" (emphasis added, p. 304). These changes in friend selection beget changes to one's degree of *pro*social capital, with consequences for later involvement with delinquency. Consistent with this idea is research by Giordano and colleagues (2004) on desistance; in this study, former offenders who successfully avoided recidivism described purposefully selecting out of friendships with deviant others and selecting into prosocial connections.

More evidence for the role of peer selection, and its potential link to decision-making, is found in programs designed to change how adolescents select friendships, rather than to decrease adolescent susceptibility to deviant peer influence. Given the evidence that peer selection is impactful, it is no surprise that many effective interventions encourage adolescents to select prosocial, rather than deviant, friendships and peer groups (Botvin & Griffin, 2004; Ellickson et al., 200; Hansen & Dusenbury, 2004). As an example, school districts randomly assigned to receive the

PROSPER intervention, which employed a number of these programs, found changes in friendship network structure compared to control districts. Specifically, antisocial adolescents occupied less central network positions after the intervention (Osgood et al., 2013a). This suggests that friend selection is malleable and open to change through interventions that include decision-making, problem-solving, and deviant peer resistance components, as is the case in PROSPER. It also highlights how enhanced decision-making and problem-solving skills, similar to TRDM, may play a role in friendship selection.

Prosocial Peers

It is not just selecting out of friendships with deviant others that matters, but also selecting into friendships with others who are not involved in delinquency (prosocial peers). It is possible for adolescents to select out of delinquent peer groups without selecting new friends, but this is not as desirable as having prosocial ties; social isolates do not have an increased risk of delinquency in all contexts, but often suffer other negative outcomes (DeMuth, 2004; Kreager, 2004). Replacing deviant peers with prosocial friends was also qualitatively described as important by the participants of Giordano and colleagues (2004). Similarly, Wright and Cullen (2004) argued employment promoted desistance indirectly, through encouraging association with positive peers and decreasing association with deviant ones.

Few quantitative empirical inquiries in criminology have established whether prosocial friends are protective against delinquency, despite the vast literature establishing the negative impact of deviant friends. A few have found evidence that the lack of delinquency amongst friends predicts future behavior. Adamczyk-

Robinette and colleagues (2002) found that adolescents whose peers did not use tobacco were much less likely to use tobacco themselves, amplifying the impact of other promotive factors. Another notable example is McGloin's (2009) theory of delinquency balance, which found positive influence by friends who are relatively less delinquent. In this paper, McGloin (2009) used longitudinal panel data from Add Health to demonstrate that it is not just the deviance of the friend, but the relative deviance of the friend, that matters. Specifically, adolescents attempted to achieve *balance* in delinquency by modifying their level of crime to be in line with that of their friends. She found that peers less deviant than the adolescents had a relatively prosocial impact on adolescents' behavior, reducing the amount of crime they committed (see also Boxer et al., 2005).

Here, prosocial peer influence refers to the lack of deviance amongst friends. Other researchers find that peer's engagement in prosocial behavior (such as getting good grades or involvement in conventional clubs and activities) or providing prosocial feedback to an adolescent's behavior also plays an integral role in the facilitation of prosocial behaviors. Prinstein and colleagues (2001) found that the higher the proportion of an adolescent's friends that engaged in prosocial behavior, the less likely the adolescent was to engage in violence and substance use. Barry and Wentzel (2006) outlined a process whereby adolescents were influenced by their friends' behavior to pursue prosocial goals, which, in turn, led to increased prosocial behavior. Thus, prosocial influence, either defined as the lack of deviant behaviors or the presence of prosocial behavior, exerts an influence in ways similar to deviant peer

influence. Some evidence suggests prosocial influence to be relatively stronger than deviant peer influence (Carson, 2013; McGloin, 2009).

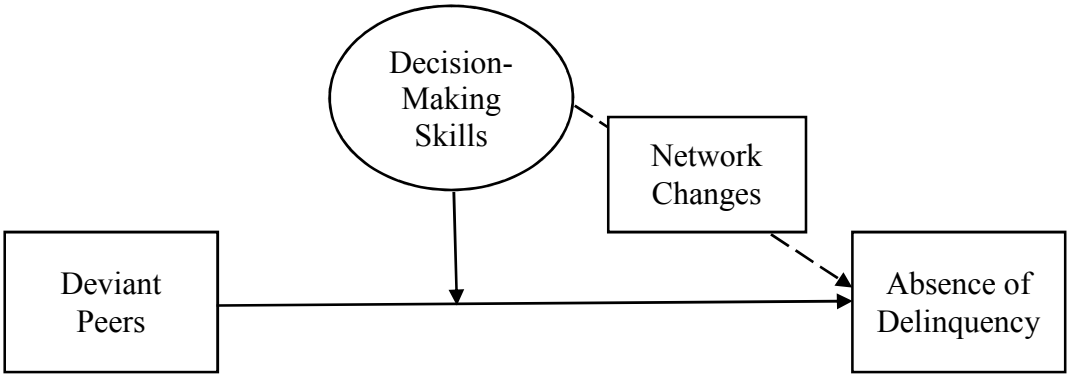
Non-deviant peers are an important form of social capital that is just as influential, if not more influential, than deviant peers. It stands to reason that the accumulation of this form of social capital would act as a promotive or protective factor. Brechwald and Prinstein (2011) concluded that "peer socialization processes also may provide potential protection from maladaptative outcomes" (p. 167), while Garrido and Taussig (2013) found that the relationship between exposure to intimate partner violence and experiencing teen dating violence disappeared for the adolescents with a high level of prosocial peers, illustrating its potential to act as a protective factor. As peer selection may be especially influential during young adolescence (Vitória et al., 2020), prosocial peer selection may be especially protective. Engaging in rational decision-making processes, such as TRDM, encourages actors to "opt in" to such prosocial forms of capital, which would have cumulative impacts on the adolescent's tendency to avoid delinquency; yet, the relationship between deviant peer exposure, TRDM, selection into prosocial peer groups, and delinquency remains unexamined.

Present Study

The present study leverages structural equation modeling to capture the potential direct and indirect effects of decision-making skills on the relationship between deviant peer normative influence and resilience regarding adolescent delinquency. Deviant peers are known to be one of the strongest, most consistent predictors of one's own delinquency (Pratt et al., 2010; Warr, 2002), especially

among adolescents (Steinberg & Monahan, 2007), yet not all who have deviant peers will commit crime. Agentic actors may utilize decision-making skills to avoid this common pitfall into delinquency (Paternoster & Pogarsky, 2009). The present study seeks to identify direct and indirect role of TRDM in encouraging resilience to deviant peer influence (see Figure 1).

Figure 1. Theoretical Structure of Hypothesized Role of Decision-Making in Resilience to Deviant Peer Influence



Solid lines denote direct pathways. Dotted lines denote indirect pathways through another variable. Circles represent latent constructs, while squares represent observed variables.

First, this study examines whether decision-making skills *directly* promote resilience to peer influence (Botvin et al., 1998; Gardner et al., 2008; Goodnight et al., 2006). Specifically, individuals who engage in a more thoughtful, reflective process when deciding on action may be more likely to avoid the draw of peers towards preference for risk and reward and the prioritization of peers over future goal-directed behavior. TRDM encourages not only going through a rational process, but coming to better decisions on average than those who do not (Paternoster et al., 2011). These adolescents would be more likely to select prosocial behaviors that will have positive consequences in the long-term. Thus, undergoing a slow and reflective

decision-making process may improve adolescent's outcomes in the presence of deviant peer influence (Paternoster & Pogarsky, 2009).

- *Hypothesis 1: TRDM will be positively associated with resilience to deviant peers.*
- *Hypothesis 2: TRDM will be more protective at higher levels of deviant peer exposure.*
    - *Hypothesis 2a: The interaction between deviant peer exposure and TRDM will have a positive association with resilience.*
    - *Hypothesis 2b: The positive association of TRDM with resilience will be larger in magnitude for adolescents with a higher level of deviant peer exposure in the multigroup models.*

Second, this study examines whether decision-making skills *indirectly* promote resilience through selection of prosocial capital – specifically, opting into friendships with prosocial peers. According to Luthar (2006), personal assets with the highest "promotive potential" (or the most beneficial to resilience) are those that are "generative of other assets, catalyzing or setting into motion other strengths and mitigating vulnerabilities" (p. 781). Whether or not TRDM directly protects against deviant peer influence, adolescents with TRDM can engender change in their own social networks; accordingly, TRDM is associated with building prosocial forms of human, social, and cultural capital, and these forms of capital somewhat explain the relationship between TRDM and better life outcomes (Paternoster et al., 2011). In this case, adolescents can shape their environment over time. That is, those who make better decisions (a personal asset) will tend to opt-in to positive environmental

resources over time, likely recognizing the risks around them and making the decision to both improve their environment and their long-term outcomes.

- *Hypothesis 3: The relationship between TRDM and resilience will be mediated by changes in the adolescents' friendship networks.*
    - *Hypothesis 3a: TRDM will be negatively associated with the change in exposure to deviant peers.*
    - *Hypothesis 3b: The change in deviant peer exposure will be negatively associated with resilience.*
    - *Hypothesis 3c: The indirect effect of TRDM through the change in deviant peer proportion on resilience will at least partially explain the protective impact of TRDM.*

CHAPTER 3: DATA AND METHODS

Data Sources and Sample Selection

In the current study, I use a panel dataset with social network information from the PROmoting School-community-university Partnerships to Enhance Resilience (PROSPER) intervention (Spoth et al., 2007). Specifically, I will use data gleaned from the PROSPER Peers dataset. Due to its collection of social network information, this dataset is well-suited to answer the present research questions. Due to its focus on rural adolescents, I can use this data to examine the relationship between decision-making skills and resilience to peer influence in an understudied population. The rural school districts included in this study are gleaned from areas where the population is, on average, about 19,000 (the smallest was about 7,000, while the largest about 45,000). Thus, the majority of the schools come from small population areas; only 5 schools had half of their population come from urbanized areas of 50,000 or more.

The PROSPER Peers population includes twenty-eight public school districts in rural towns and (semi-rural) small cities, fourteen in Iowa and fourteen in Pennsylvania. The dataset was collected to test the PROSPER intervention's short and long-term effects on student outcomes. Initial eligibility criteria included 1) school district enrollment between 1300 and 5200 students, 2) eligibility for free or reduced-cost school lunches among least 15% of the students in the school, and 3) a student population that was at least 95% English-speaking. School districts were first grouped based on their size and geographic locations, then randomly assigned to be a

member of either the control (normal school programming) or experimental (implementing PROSPER intervention) condition.

Data collection employed a cohort sequential design that included two cohorts of 6th graders, one in 2002 and the other in 2003. The first wave of data collection was collected in the fall semester of 6th grade (for pre/posttest intervention purposes), with a second wave of data collection in the spring of 6th grade. Another wave of data was collected annually in the spring of each following year, from 7th grade up to 12th grade, for a total of eight waves. In this dissertation, I use data from the middle six waves, following adolescents from the spring of grade 6 to the spring of grade 11.[10] Specifically, I run separate structural equation models (SEM) for each consecutive set of three waves for a total of four sets: 6th – 8th grade, 7th – 9th grade, 8th – 10th grade, and 9th – 11th grade.

Data Collection

For this project, I use the PROSPER Peers in-school data. Students in these schools were given a self-report questionnaire covering many different topics, including delinquency, decision-making, and in-school friendships. On the collection day, the in-school survey was distributed to all students who were English-speaking and did not have any severe cognitive disabilities. The survey was distributed by a

[10] This first wave is excluded from the analyses to keep the time between waves consistent. The time between the first and second waves is only 6 months. Including this wave would confound the results, as any change in the parameters over time (hypothesized to be due to age) could also be due to the shortened time frame between waves. From hereafter, the second wave collected by PROSPER Peers will be referred to as the first wave/Wave 1. The last wave (12th grade) is excluded from the analyses as many schools had very low response rates at this wave, calling the accuracy of the social network information into question.

member of the research staff during one class period without a teacher present. Students were assured of confidentiality and informed that their responses would not be reviewed by a teacher or parent. Students (and their parents) were given the option to refuse participation at each wave.

There was some attrition over the course of the six waves, but any attrition was driven primarily from people moving out of the school districts. Students had to stay in the school in order to be included in the population, so students who moved or switched schools were no longer included. Students who participated in the first wave participated for an average of 4 waves. There were students added in each wave, as students who joined the school during the data collection period were added to the population. Across the twenty-eight school districts, participation rates averaged about 88% for an average of about 9,000 students per wave (the specific participation rates and numbers varied by wave). In each model, each pair of variables on which the participant provided information will be used, even if the adolescents are not in the sample at other waves (pairwise deletion). Thus, adolescents are only excluded from the analyses for which they were not in the school for any of the three waves, did not report usable information for any pairs of variables across the three waves, or do not fit the intended sample (described in the next section).[11] In order to examine bias due to attrition, I will conduct a sensitivity analysis comparing the model results for adolescents who are in every wave to the results using the full sample.

[11] PROSPER researchers made multiple attempts to reach students that were missing from the sample due to absence from school. Thus, any students missing due to absence were likely rarely in school, and any inferences drawn from these students and their social network data would likely be unreliable.

Sample Selection

For the purposes of the present study, participants had to meet additional qualifications at each starting wave in order to be included in each analyzed sample. First, given the focus on exposure to deviant peers, information about the participant's friend(s) was required. Thus, the students had to complete the survey and nominate friends (69% of surveys).[12] The students were asked to nominate up to two best friends and up to five other friends from their grade in the school at the very end of the survey. Students included in this study could have missing data on other variables but must have nominated at least one friend – in other words, given the focus of this inquiry, social isolates are excluded from the sample.

Second, given the focus on resilience to deviant peer exposure, the participants had to demonstrate exposure to the risk factor at hand (i.e. exposure to at least one deviant peer).[13] This meant that, of the friends that the participant nominated, at least one friend had to have filled out his/her own survey and reported information about his/her own level of deviance.[14] Lastly, at least one friend had to

[12] Three of the twenty-eight school districts did not have reliable network data and were thus excluded from the sample at this point. One school did not allow collection of friendship data, another school district had a fire, and another school (in one cohort only, with the other cohort still included) was missing the network data at one wave because of survey time concerns. These schools are omitted from this analysis and all other analyses hereafter.

[13] While one deviant friend may not appear to place someone at "high risk" for deviant behavior, researchers have found evidence of deviant peer influence from a single friend (for example, a best friend; Urberg et al., 1997; Weerman & Smeenk, 2005). This definition of risk helps mitigate concerns about regression to the mean, as longitudinal studies focused primarily on groups exposed to a high-level of the risk factor may find improvement over time due only to this statistical artifact (Fergus & Zimmerman, 2005). Additionally, multigroup analyses allow for an examination of differences in parameters by four different levels of deviant peer exposure (as discussed in section on analytic plan).

[14] The listed friends were matched to other surveys by two coders (assisted by a computer program that suggested potential matches) using existing student rosters. Friends whose name was not found on the existing student roster or partial names for which there could be multiple possibilities could not be matched. An average of 82% of the listed friends could be successfully matched to another student on the student roster that completed the survey.

have reported at least one act of delinquency. This is due to the focus on resilience, which is defined by a positive adaptation to exposure to a risk factor (Luthar, 2006) – in this study, deviant peer influence. Avoiding delinquency without any exposure to friends' deviance cannot be considered resilience. Thus, participants require at least some degree of exposure to deviant peer influence at the starting wave of each analysis in order to test for resilience in later waves.

Combined, these sample selection strategies led to an average of 5,996 students per wave. The original analytic sample[15] averaged 9,014 students per wave (with a total of 54,082 student/year observations), but this sample was reduced due to the requirements of my model. Another 11.11% of the sample was removed for not reporting any friends.[16] For those subjects who did nominate friends, another 2.39% were removed for failing to have any matched data on the deviance of their friends. Lastly, another 23.33% of observations were excluded for having no reported deviant friends at that wave, given that exposure to the risk factor at hand (deviant peers) is required in order to study resilience.

The full sample and my selected sample did have differences on the variables used in my analyses, but differences are small for all variables not related to the friendship network (see Table 1). My research questions focus on adolescents who have friends and are exposed to deviant peers. Including adolescents with no friends

[15] The analytic sample excludes students who refused the survey, did not finish the survey, or were absent on the day data was collected (Jacobsen, 2020). This excludes about 26% of the original population.

[16] Ostensibly, these students did not have friends. The questions about friendship networks are at the end of the survey, and these students completed at least 14 of the last 16 survey items before failing to nominate friends. This supports the interpretation that these adolescents did not have friends and thus are appropriately excluded from my sample. However, some of these students may have finished the survey but opted not to answer this specific question despite having friends; I cannot distinguish between the two.

or no deviant friends would be inappropriate as they do not represent my population of interest for this study; the loss of this data thus does not represent "missing" data and is consistent with other PROSPER Peers research studying peer networks (Kreager et al., 2011). Differences in measures of deviance and friend characteristics are expected. Accordingly, adolescents in my analytic sample nominated more friends – of which a larger proportion was deviant, leading to a slight decrease in the proportion of deviant friends in the next wave – and spent more time socializing with them in an unstructured, unsupervised manner.

My sample also had statistically significant differences on control variables and the outcome. Small differences on these variables are not surprising, as the sample was selected based on having friends and exposure to deviant peers. Although some of these differences may be statistically significant, they are not substantively large. That is, the statistical significance may be more a product of the large sample sizes (at least 4,500 students in each group) than the product of important differences between the control variables. For example, given a range from 1-5 and an SD of .67 and 1.35 respectively, a .03 difference in parental monitoring and a .04 difference in impulsivity are not likely to represent large modeling differences. My sample does tend to be comprised of more males, which may be a product of more exposure to deviant friends among males on average (Piquero et al., 2005). Differences in dichotomous measures of prior delinquency and future delinquency (the outcome variable) differ about 3-4%, but these differences are expected given the two group's disparate levels of risk (i.e., exposure to deviant peers).

Table 1. Descriptive Statistics in Full versus Included Sample at Starting Wave

	Full Sample			*Included Sample*		
	Mean or %	SD	N	Mean or %	SD	N
No Delinquency[a]***	58.44%	--	6,983	54.82%	--	4,571
Δ DP Proportion[b] ***	.06	.34	6,333	-.03	.33	4,534
DP Proportion***	.34	.30	8,014	.47	.25	5,718
TRDM*	.13	.96	8,582	.10	.95	5,557
Prior deviance***	34.01%	--	8,827	37.13%	--	5,705
Male***	48.41%	--	8,829	52.35%	--	5,712
White***	86.17%	--	8,640	86.61%	--	5,578
Free Lunch	-.17	1.66	8,832	-.19	1.64	5,712
Parental Monitoring*	4.46	.67	8,715	4.43	.67	5,641
Parent Relations*	.10	.39	8,731	.08	.39	5,657
Impulsivity*	2.51	1.37	8,623	2.55	1.35	8,623
UUS***	6.89	3.21	8,256	7.18	3.22	5,650
# of Nominations***	4.58	2.30	8,844	5.34	1.76	5,718
Tx Condition***	45.12%	--	8,844	45.02%	--	5,718

DP refers to Deviant Peers. UUS refers to unsupervised, unstructured socializing. Δ signifies change. [a] Measured at Time 3. [b]Measured at Time 2. * $p < .05$ ** $p < .01$ *** = $p < .000$ in a dependent sample t-test or McNemar test between the full analytic sample and the subjects included in the current sample.

Measures and Descriptive Statistics

A list of descriptive statistics for all included variables across each starting wave of the sample can be found in Table 2.

Table 2. Descriptive Statistics for Variables Used in Analyses across Waves

Start – End Wave		*6th – 8th grade*		*7th – 9th grade*		*8th – 10th grade*		*9th – 11th grade*	
	Range	Mean or %	SD	Mean or %	SD	Mean or %	SD	Mean or %	SD
No Delinquency [a]	0, 1	54.82%	--	55.25%	--	55.49%	--	58.80%	--
Δ DP Proportion [b]	-1, .86	-.03	.33	-.01	.33	-.06	.33	-.06	.34
DP Proportion	.14, 1	.47	.25	.51	.26	.55	.26	.56	.27
TRDM	-2.24, 1.24	.10	.95	-.06	.98	-.07	.96	-.06	.93
Prior deviance	0, 1	37.13%	--	42.30%	--	47.46%	--	47.02%	--
Male	0, 1	52.35%	--	49.92%	--	49.07%	--	47.30%	--
White	0, 1	86.61%	--	85.37%	--	84.75%	--	84.82%	--
Free Lunch	-1.76, 3.43	-.19	1.64	-.20	1.64	-.21	1.65	-.28	1.61
Parental Monitoring	1, 5	4.43	.67	4.33	.71	4.21	.76	4.08	.79
Parent Relations	-1.40, .83	.08	.39	-.01	.42	-.09	.42	-.15	.41
Impulsivity	1, 5	2.55	1.35	2.58	1.26	2.70	1.21	2.77	1.17
UUS	1, 13.23	7.18	3.22	7.10	3.00	7.11	2.81	7.09	2.69
# of Nominations	1, 7	5.34	1.76	5.35	1.74	5.22	1.74	4.92	1.81
Tx Condition	0,1	45.02%	--	40.68%	--	41.70%	--	42.06%	--
--									
N		5,718		6,851		7,318		6,577	

DP refers to Deviant Peers. Δ signifies change. [a]Measured at Time 3. [b]Measured at Time 2.

Dependent Variable

The main dependent variable of interest is resilience to deviant peer influence. Given the need for proper temporal ordering of all concepts while controlling for prior behavior, each model spans three waves, with resilience measured at Time 3. A one-to-two year lag is consistent with longitudinal analyses the impact of deviant peer exposure (Haynie, 2002; Thomas & McGloin, 2013) and the more immediate outcomes of TRDM (Paternoster & Pogarsky, 2009).

Resilience in this context is defined as the absence of any delinquency. Adolescent resilience is thus measured using a dichotomous measure where 0 = any delinquency and 1 = no delinquency. Although the shortcomings of dichotomous outcome variables are well-documented (see Sweeten, 2012), the current research question is not concerned with offending seriousness or frequency, but rather whether the adolescent avoids offending in the face of exposure to deviant peers. Therefore, the correct operationalization of resilience is a dichotomous variable representing whether the adolescent engaged in any delinquency.

The dichotomous variable was generated from a scale of 9 items derived from Elliott and colleagues (1989). The participants were asked how often during the last 12 months – on a scale from never (1) to five or more times (5) – they had:

- Taken something worth less than $25 that didn't belong to them
- Taken something worth $25 or more that didn't belong to them
- Purposely damaged or destroyed property that did not belong to them
- Broken into or tried to break into a building just for fun or to look around
- Taken something from a store that they did not pay for

- Avoided paying for things such as movies, rides, food, or computer services
- Beat up someone or physically fought with someone because they made you angry (other than just playing around)
- Thrown objects such as rocks or bottles at people to hurt or scare them
- Carried a hidden weapon

Scale items that measured whether the adolescent ran away from home or skipped school without an excuse were excluded as they do not adequately represent criminal activity. An item that measured whether adolescents were picked up by the police was removed to avoid conflating the experience of formal sanctions with the commission of delinquent acts, though this item was included separately as a control for arrest in sensitivity analyses.

Some delinquency is considered typical in adolescence. As Moffit (1993) stated, "actual rates of illegal behavior soar so high during adolescence participation in delinquency appears to be a normal part of teen life" (p. 675). Moffit (1993) elaborated that during adolescence, there is a "maturity gap" where adolescents feel ready to take on more adult roles, but they are legally and socially constrained from this form of maturity. During this period, most youths engage in temporary delinquent behaviors due to "social mimicry" of other youths that exhibit stable antisocial behavior. Delinquent behavior becomes desirable as it signals maturity; delinquent behavior then falls away with increased age and access to adult roles. While there are adolescents that abstain from delinquency completely, Moffit (1993) argued that the best-adjusted adolescents engage in delinquency temporarily.

A definition of "resilience" that involves complete absence of delinquent behaviors can thus be seen as overly restrictive. Yet, this scale of behaviors involves relatively undesirable forms of delinquency – things that could lead to felony charges for larceny, assault, or burglary. I omitted the least serious delinquency measures and the quite common experience of adolescent smoking and alcohol use. While some involvement with these forms of delinquency may be "normal," it is not desirable, and the altered life circumstances for someone convicted of these crimes could be detrimental enough to ensnare adolescents in more persistent forms of deviant behavior (Moffit, 1993). Over half of my selected sample did, in fact, abstain from all these behaviors, despite exposure to deviant peers (see Table 2). Thus, I maintain that the absence of these delinquent behaviors appropriately captures resilience in this group. Even so, I conduct sensitivity analyses with only the most serious and rare delinquency items included as part of the dichotomous outcome measure.

Independent Variables

Decision-Making Skills (TRDM)

The subjects' level of thoughtfully reflective decision-making (TRDM) is measured using a decision-making scale initially developed by Wills (1986). This scale is similar in nature to the scale used by Paternoster and colleagues' (2009, 2011) operationalization of TRDM from the Add Health data, which asked to what degree the adolescents agreed that: (1) when they had a problem to solve, one of the first things they did is get as many facts about the problem as possible, (2) when they are attempting to find a solution to a problem, they usually try to think of as many different approaches to the problem as possible, (3) when making decisions, they

generally use a systematic method for judging and comparing alternatives, (4) after carrying out a solution to a problem, they usually try to analyze what went right and what went wrong.[17]

The TRDM scale included a series of five questions asked the students how often – from never (1) to always (5) – they did the following when they had a problem:

- Get information that is needed to deal with the problem
- Think about which of the choices is best
- Think about the risks of different ways to deal with the problem
- Think about the possible consequences of each choice
- Compromise to get something positive from the situation

In order to examine whether these items represent a unidimensional construct, I conducted an exploratory factor analysis (EFA). Because the assumption of multivariate normality amongst the scale items is rejected [Doornik-Hanson test; $\chi^2(10) = 8514.64$, $p = .000$], I used principal factors extraction method (see Fabrigar et al., 1999). The EFA extracted 2 factors from the 5 scale items, but the greatest break between consecutive eigenvalues was between the first and second factors, supporting a one-factor model (a common decision rule used in the Scree Test; see Nunnally, 1967). All scale items loaded above .70 onto the single factor. Likewise,

[17] The measures of TRDM used in the PROSPER Peers dataset do not adequately capture the last "reflective" portion of TRDM, or one's tendency to look back after the decision to reflect upon the quality of the decision and its outcomes (Paternoster & Pogarsky, 2009). This is a limitation, especially as engaging in reflection is known to aid persons in improving their decision-making styles over time (Ramsay & Rostain, 2008); however, given the close similarity of the existing measures and Paternoster and Pogarsky's (2009) findings that their measures of TRDM represented one unidimensional construct, I maintain that this operationalization captures TRDM.

Chronbach's alpha suggested high internal consistency for the items (α = .93). Given these results, which support the scale's unidimensionality and reliability, the factor is used for descriptive analyses (see Table 2) and structural equation models, including moderation and moderated mediation analyses. Descriptive statistics for individual items and factor loadings for each item can be found in Table 3.

Table 3. Descriptive Statistics for Indicators of TRDM Factor

	Mean	SD	N	% Missing	Factor Loading
How often do you…					
Get information that is needed to deal with the problem	3.32	1.24	26,116	1.31%	.74
Think about which of the choices is best	3.63	1.20	26,105	1.36%	.88
Think about the risks of different ways to deal with the problem	3.56	1.22	26,023	1.67%	.91
Think about the possible consequences of each choice	3.59	1.24	26,017	1.69%	.89
Compromise to get something positive from the situation	3.52	1.21	25,958	1.91%	.84

All items scored from 1 (Never) to 5 (Always)

Deviant Peer Exposure

Deviant peer exposure was operationalized as the proportion of an adolescent's friends that displayed any delinquency. Adolescent's friendship networks were defined as the friends that the adolescents nominated (i.e. the send network; Haynie, 2002). At each wave, students were asked to name up to two best friends and five other friends, for a total of up to seven friends. Friends were defined as delinquent if they reported committing at least one of the 9 delinquent acts over the past 12 months. For each friend with information about deviant behavior, a dichotomous variable representing whether they had engaged in any delinquency (= 1) or not (= 0) at that wave was generated, followed by a variable representing the

proportion of nominated friends that displayed any delinquency (from .14 – 1).[18] In models using the multigroup method to examine the interaction between TRDM and level of deviant peers, this variable is used to divide the sample into groups defined as low (over 0 but less than 40%), mid (from 40-60%), high (over 60% but less than 100%), and all (100%) deviant peer exposure.

This operationalization relies on the delinquency reported by each of the adolescent's friends, rather than adolescent's perceptions of their friends' delinquency. This alleviates concerns over adolescents' misperceptions or misrepresentations of their friends' behavior. Most importantly, it eliminates bias due to projection – adolescents projecting their own behavior onto their perceptions of their friend's behavior. Also called the "influence of assumed similarity," there has been some criticism of perceptual measures of friend's delinquency for this reason (Gottfredson & Hirschi, 1990; Jussim & Osgood, 1989; Young et al., 2011, 2014). However, perceived peer delinquency does not appear to reflect *only* projections (Boman & Ward, 2014; McGloin & Thomas, 2016). Friend-reported measures of peer delinquency may be lower in construct validity because, in order for normative influence to have taken place, it is necessary for adolescents not only to have delinquent friends but also to perceive those friends as delinquent. Thus, a weakness of the current approach is the inability to capture whether or not adolescents' perceptions resemble their friends' reported levels of delinquency.

[18] The proportion does not include 0 because adolescents with no deviant friends at the starting wave (Time 1) were systematically excluded from the analysis. Adolescents were included in the analyses if they had deviant friends at Time 1 but had no deviant friends at Times 2 or 3.

This measure of deviant peer exposure is relative, assessing the ratio of delinquent to non-delinquent friends in the adolescent's network. This relative operationalization of peer influence is consistent with Sutherland's (1947) and Akers' (1973) focus on differential association, or the relative ratio of attitudes favorable versus unfavorable to crime. Research on social learning theory generally finds the principle of differential association to be the measure that exerts the largest and most consistent impact on one's later delinquency (Pratt et al., 2010). Haynie (2002) explored whether the proportion of a network that engages in delinquency is a better predictor of future behavior than the absolute amount of delinquency among the peers in an individuals' network. Haynie (2002) argued: "Assuming that delinquent friends provide favorable definitions and modeling of delinquent behavior and non-delinquent friends provide unfavorable definitions and modeling of prosocial behavior, the proportion of delinquent friends may be more important than the frequency of delinquent acts committed by friends" (p. 106). Using the Add Health data, Haynie (2002) supported her hypothesis, showing that, when included together, the proportion of delinquent friends significantly predicts an individuals' delinquency, while the absolute level does not.

Mediating Variable

In order to measure the change in the deviance of the adolescent's friendship networks from Time 1 to Time 2, I created a measure of change in deviant peer exposure. Deviant peer exposure was measured as the proportion of the adolescent's friends that displayed any deviance (discussed in more detail in the previous section). I then calculated a change score for deviant peer exposure by subtracting the deviant

peer proportion at the first wave in sequence (Time 1) from that of the next wave in sequence (Time 2). Thus, positive values indicated that adolescents had a larger proportion of deviant friends than they had in the wave prior, while negative values indicated that adolescents now had a smaller proportion of deviant friends.

Control Variables

All analyses controlled for demographic characteristics, PROSPER treatment condition, characteristics of the friendship network, impulsivity, parenting characteristics, and prior delinquency measured at Time 1. These variables have the potential to impact not only resilience, but also change to deviant friend groups. Demographic characteristics known to be consistent predictors of criminal behavior and friendship networks include gender (male/female), race (white/non-white), and socioeconomic status (free/reduced-price lunch). The PROSPER Peers dataset did include more specific racial categories – separating Black, Hispanic, and Other – however, given that most of the sample was white (85%), treating the variable as categorical could lead to insufficient power to detect significant differences between racial categories.

Socioeconomic status is measured using whether they received free or reduced-price lunch. At each wave, students were asked what they did for lunch on school days. The variable was coded as a dummy variable, where 1 = indicated that they received a free or reduced-price lunch and 0 = any other response. This measure of socioeconomic status is criticized because some students who are eligible may neglect to sign up, especially as the get older, for fear of stigmatization (Sirin, 2005). Additionally, the use of a binary measure to measure socioeconomic status may not

sufficiently capture a complex construct (Harwell & LeBeau, 2010). However, Osgood, Baals, & Ramirez (unpublished) used PROSPER Peers data to create an aggregate, longitudinal version of the free-reduced-price lunch measure. The authors developed empirical Bayes shrinkage HLM estimates using all available data for adolescents across years to develop one fixed measure representing socioeconomic disadvantage. Comparing this free/reduced price lunch to household income, mother's education, and household composition, the authors find this measure to operate similarly. This empirical Bayes measure is found to be more strongly related to the expected correlates and outcomes than the original dichotomous measure (Baals, 2018; Osgood et al., unpublished). Thus, I use this measure to control for socioeconomic status.

Treatment condition (1 = assigned to intervention condition and 0 = assigned to control group) represented the half of the schools that utilized community teams to implement a variety of evidence-based family-focused and school interventions. These interventions did intend to contribute to decision-making and problem-solving skills and improve prosocial friendship selection (see Osgood et al., 2013a), therefore it is important to control for whether or not the student was in a school that received the PROSPER intervention (Spoth et al., 2007).

The analyses will also control for two features of the friendship network – the number of friendship nominations made and unstructured, unsupervised socializing with friends – in order to avoid confounding the impact of deviant peer exposure with mechanisms outside of normative influence. Measures of deviant peer exposure can be dependent on the number of friendship nominations made by the adolescent, and

between-person comparisons of the strength of deviant peer influence can be distorted without considering the impact of the number of friends (Osgood & McMillan, 2019). As an example, I observed that students in the present sample with more friends tend to have a lower proportion of deviant friends. I thus included a continuous measure of the number of friendship nominations each student made to statistically account for covariance between number of friends and deviant peer exposure.

In addition to socialization, spending time with friends in unsupervised, unstructured contexts has a criminogenic effect of its own, perhaps equal to or greater than the socialization effect magnitude (Haynie & Osgood, 2005). Osgood and colleagues (1996) found that unsupervised time spent with peers provides an environment conducive to offending, including the presence of rewarding criminal opportunities. It is necessary to include a measure of time spent with friends in this context to avoiding confounding the influence of deviant peers with the opportunities afforded by spending time with them. The measure of unsupervised, unsupervised socializing (UUS) is based on the question "How often do you spend time just hanging out with this person outside of school (without adults around)?" scored from never (1) to almost every day (5). The measure does not distinguish independent time spent with each friend from time spent in a group, which can overestimate the time adolescents spend with their friends if used in an additive way. Yet, taking the average score across friends makes the assumption that adolescents with more friends do not spend more time socializing. As a compromise, I created an additive measure of UUS across all friends and then divided by the square root of the number of friends (see Haynie & Osgood, 2005).

A control for impulsivity is included here to control for spurious effects with TRDM. The impulsivity measure was gleaned from a one-item measure asking respondents "How often do you do what feels good, regardless of the consequences?" scored from never (1) to always (5). This was initially a member of three items initially designed to measure sensation seeking (Zuckerman, 1994). However, this item is conceptually very similar to impulsivity, a preference for immediate gratification, which has been found to exert consistent, sizable impacts on criminal behavior (Arneklev et al., 1999; Burt et al., 2014). Impulsivity has been found conceptually and empirically different from sensation/risk-seeking behaviors; for example, Steinberg and colleagues' (2008) dual-process model postulates that impulsivity and risk-seeking are different constructs that have different neurological underpinnings and develop at different rates throughout adolescence. I conducted tests of the three items' internal consistency, finding it to be improved by excluding the impulsivity item from the other two measures of sensation-seeking ($\alpha = .85$ compared to $\alpha = .78$).

Similar to the findings of Paternoster and Pogarsky (2009) using the AddHealth data, this measure of impulsivity and the measures of TRDM are empirically distinct constructs in the PROSPER data. The highest correlation between this item of impulsivity and the five measures of TRDM is -.11, while the lowest correlation among the TRDM items is .63. Including the impulsivity measure in a six-item factor analysis produces a one factor model; however, the impulsivity measure is the only item that does not load onto that factor (loading of -0.10, compared to TRDM items with factor loadings .74 and above). Further, the internal consistency of

the items is greater with the impulsivity items excluded (α = .87 compared to α = .93). This leads to the conclusion that impulsivity and TRDM are best understood as independent constructs. In addition, the measures are conceptually distinct as well – whereas the TRDM measures ask questions about whether individuals gather information, select an option, consider the risks and consequences, and compromise to find the best solution to a given problem, the impulsivity measure captures the urge for immediate gratification or the appeal of present rewards for the adolescents.

Parenting is a consistent correlate of crime and can impact adolescent's exposure to and influence from deviant peer influence (Chung & Steinberg, 2006; Elliott et al., 1985; Farrington, 1986; Warr, 2002). Good parenting represents an important protective resource in an adolescent's environment, encouraging resilience to risk factors (Fergus & Zimmerman, 2005). As such, I control for parental monitoring and parent relations. Parental monitoring was measured as the mean of 5 items (α = .83), including "during the day my parents know where I am" and "my parents know who I am with when I am away from home", measured using a Likert scale from never (1) to always (5). Parent relations was measured using a mean of standardized subscales (α = .94) that measure affective quality between parents and children ("during the past month, when you & your dad have spent time talking or doing things together, how often did he act loving & affectionate toward you?"), joint activities with parents ("during the past month, how often did you work on homework or a school project together with your mom or dad?"), and parental reasoning ("my parents give me reasons for their decisions"). This composite was coded so that higher scores indicate closer and more involved parents.

Lastly, I included a dichotomous measure of prior delinquency measured at Time 1, which captures whether adolescents committed any of the 9 delinquent acts (= 1) or avoided all 9 acts (= 0). Including prior delinquency allows me to measure its impact on selection into deviant peer groups and into deviant behavior and avoids overstating the impact of peer influence (Kandel, 1996). Including a lagged measure of the dependent variable does have a downside; it is typically too strong a control for peer selection and leads to understating the impact of deviant peer influence and other measured variables at work before the study period began (McGloin & Thomas, 2019; Thomas et al., 2019). Yet, studies using this technique still identify socialization effects (Haynie & Osgood, 2005; Matsueda & Anderson, 1998; McGloin et al., 2014). The inclusion of a lagged dependent variable (LDV) is particularly important in the present study, which addresses friendship selection as well as influence. A consistent predictor of the deviance of one's friends is one's own deviance (peer selection; Elliot et al., 1985; Gallupe et al., 2019; Osgood et al., 2013b, 2015; Ragan, 2020; Thornberry, 1987); therefore it is important to control for peer selection based on behavioral similarity in order to isolate peer selection due to TRDM. However, as LDVs tend to underestimate the impact of peer socialization since they cannot account for concurrent influence and tend to underestimate delayed peer influence, I will also conduct sensitivity analyses excluding this variable; the estimates while controlling for LDV will represent a "lower bound" of effects while those without will serve as the "upper bound" (see Haynie & Osgood, 2005).

The present study utilizes a limited number of control variables compared to many studies in criminology due to theoretical and methodological concerns. It is

difficult and inadvisable to control for all known risk factors for crime; there "is no shortage of factors... literally thousands of variables…" (Farrington, 1992, p. 256). As Matza (1964) described, "… when factors become too numerous… we are in the hopeless position of arguing that everything matters" (p. 23-24). A theoretically informed, parsimonious version of the model may advance theory more than including all available variables in the model (i.e. the "kitchen sink" model; see also Wikström, 2007).

Many researchers in the field of normative influence often include variables from competing theories – most notably, social control variables due to theoretical debates with control theorists – in order to reduce the likelihood of finding spurious effects. Generally, the predictive power of social learning theory variables is robust to the inclusion of variables from competing theories (Pratt et al., 2010). It has been widely found that social learning variables are still influential when controlling for social control measures and using statistically sophisticated or even quasi-experimental or experimental designs (McGloin & Thomas, 2019; Paternoster et al., 2013). Although there always remains the possibility of bias from unobserved variables, "…it remains the case that a meaningful peer effect has held up against an array of attempts to account for rival explanations and model specifications" (McGloin & Thomas, 2019, p. 251).

From a methods perspective, parsimonious tests are preferred when using structural equation models (SEM). Inclusion of too many parameters runs the risk of under-identifying the model; additionally, adding more variables can also artificially inflate some model fit indices, while others will penalize more complex models (Gau,

2010). Simple models are thus more desirable despite potential penalties to overall measures of model fit (Mulaik et al., 1989). Thus, the chosen control variables are important demographic variables and/or variables that, without their inclusion, may lead to spurious or misleading results for theoretical reasons.

Analytic Plan

The analyses in this dissertation will proceed in three stages. First, I start by conducting descriptive analyses, including investigating whether there is evidence of resilience amongst deviant peer exposure and whether this depends on the degree of deviant peer influence. I will also conduct bivariate comparisons examining how adolescents who display resilience differ from those who do not. Second, I will use SEM to conduct moderation analyses to examine whether deviant peer exposure and TRDM interact to promote resilience to deviant peer influence. Third, using moderated mediation analyses, I will investigate whether TRDM has an indirect impact on resilience through prompting changes to the adolescent's social network.

The analyses will leverage the longitudinal nature of the PROSPER Peers data by carrying out the SEM models separately for each possible set of waves. As existing evidence finds processes of deviant peer influence and selection to change with age (Albert et al., 2013; Gardner & Steinburg, 2005; Steinberg & Monahan, 2007; Vitória et al., 2020), it is possible that the results of the models will change across 6^{th}-11^{th} grade. While not included as a variable of interest, the estimated models are clustered on a variable created to uniquely identify sampling groups based on the two cohorts and twenty-eight school districts; I also use robust estimates of standard error and model fit statistics. These corrections adjust standard errors for

non-independence between and within clusters due to sampling strategies (see Asparouhov, 2005; Stapleton et al., 2016). I use Stata 16 to conduct descriptive analyses (StataCorp, 2019) and Mplus Version 8.4 to conduct all structural equation models (Muthén & Muthén, 1998-2010).

Structural equation modeling (SEM) refers to a series of multiple regression models employed simultaneously to estimate complex structures of relationships between variables. SEM has its roots in factor analysis, often linked to psychology, and path analysis, widely used in econometrics and sociology. The 1970's saw these two ideas merge to allow the estimation of simultaneous equations that include latent variables (Hauser & Goldberger, 1971; Jöreskog, 1973). SEM is not so much a model, but a way of approaching estimation. Many types of analyses fall under the umbrella of SEM, including linear regression, path analysis, confirmatory factor analysis, growth structure models, and item response theory.

Path analysis, where models specify the direction and interrelationships between variables, is a fundamental building block of SEM. It's basic formulation, where M is a predictor in one but is an outcome in another, can be written to signify that X impacts M, which then goes on to impact Y:

$$Y_{i=} \beta_1 + \beta_2 M_i + \varepsilon_{1i}$$

$$M_{i=} \beta_3 + \beta_4 X_i + \varepsilon_{2i}$$

Measured and latent variable path analysis (MVPA, LVPA) allow for the testing of relationships among measured or latent variables, while confirmatory factor analysis (CFA) tests whether these specified pathways fits according to the data we observe.

SEM expanded to include CFA to measure latent variables (Jöreskog, 1973; Keesling, 1972; Wiley, 1973). Latent variables, or factors, represent unobservable constructs estimated using observable measures meant to capture the latent construct. Many of the variables in the social sciences are latent and "unmeasurable" in their true form. Thus, it is a commonly used approach in psychology and other fields in the social sciences, where researchers frequently desire to measure personality traits, behavioral tendencies, and etcetera for which there is no single, simple, objective measure. As described by Silva and colleagues (2019), using the observed measures as indicators of the underlying latent construct "eliminates item-specific variance and produces a measurement error-free construct" (p. 2).

SEM is theory-based, deductive, and aims to confirm (or disconfirm) the specified models. The model must be built on theory and tested against data. The objective is to examine whether the hypothesized relationships between variables in the model resemble the relationships observed in the dataset (Meyers et al., 2013). SEM relies on what has been entered into the model and examines the specified model's fit. If the model fits poorly, the models can be modified to attempt a closer fit between the hypothesized pathways and real-world observations.

SEM is specifically well-suited to answer the present questions for many reasons. First, SEM is flexible and ideal for cases where there are many interrelated variables requiring simultaneous equations. Using SEM, it is possible to test an "intricate structure of relationships among variables in a single model" (Silva et al., 2019, p. 2). It is ideal for testing both direct and indirect paths between variables including moderation, mediation, and models that combine the two. Second, SEM

allows for the modeling of latent variables as factors – in these analyses, TRDM is best understood as a latent construct that causes the observed levels of its indicators. Third, SEM explicitly models measurement error and covariance between exogenous variables.

Fourth, SEM has many different possible estimation techniques for the equations. In SEM, the researcher can specify which variables are categorical in order to appropriately analyze dichotomous independent and dependent variables. The weighted least squares estimator serves as the default for Mplus models with categorical dependent variables (Muthén & Muthén, 1998-2010). Weighted least squares estimators, which assumes an underlying latent distribution for categorical outcomes, have been found to have advantages over maximum likelihood for these types of dependent variables. Evidence suggests robust categorical least square estimators more accurately predict factor loadings and robust standard errors, to exhibit less bias in estimating large factor loadings, and to be more sensitive to asymmetric category thresholds compared to maximum likelihood estimators (Li, 2016; Rhemtulla et al., 2012). It is generally recommended for datasets containing categorical variables with a small categorical or dichotomous outcome (Suh, 2015). However, it is more sensitive to sample size and violations of the assumption of normality compared to robust ML estimators (Rhemtulla et al., 2012). While sample size is not a problem using the PROSPER Peers dataset, the assumption of normality will likely be challenged.

Some evidence suggests that maximum likelihood (ML) estimators, which aim to identify the population parameter values from which the observed data are

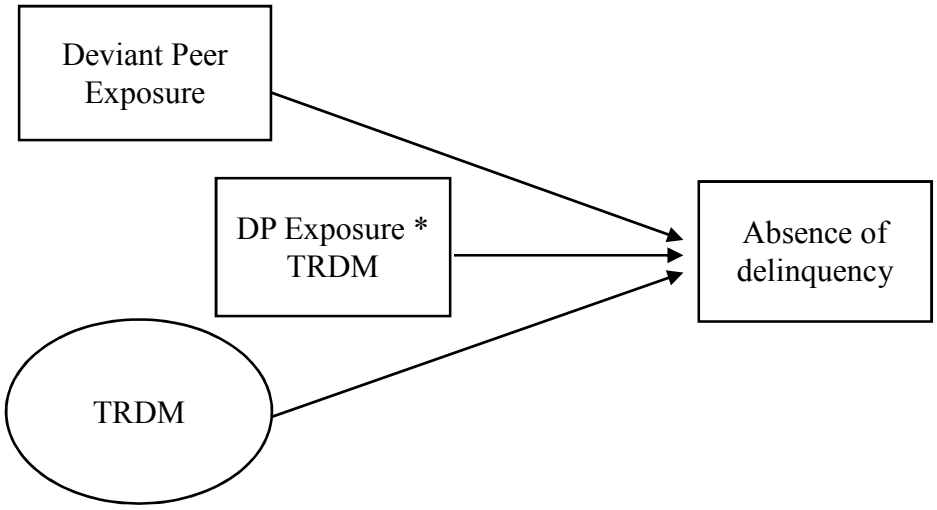
most likely to have arisen, perform similarly to weighted least squares methods with categorical outcomes (specifically ML methods with robust standard errors, aka MLR). Overall, research finds that MLR estimates, when used in conjunction with categorical outcome variables, have less power but better control Type 1 error (Bandalos, 2014; Suh, 2015). MLR also handles missing data in a way that uses all possible information to estimate parameters (Muthén et al., 2015; discussed in more detail in limitations section). The following analyses are thus also estimated using MLR methods in sensitivity analyses to investigate whether using robust maximum likelihood estimation procedures leads to any changes in results.

Moderation Analyses

A moderator is a variable that "affects the direction and/or strength of the relationship between an independent or predictor variable and a dependent or criterion variable" (Baron & Kenney, 1986, p. 1174). These analyses test whether deviant peer exposure and TRDM interact to contribute to adolescent's avoidance of delinquency (i.e., resilience). These models leverage multigroup and factor score interaction analyses. Factor score interactions measure interactions between an observed variable (proportion of deviant peer exposure) and a latent factor score (TRDM). The multigroup models determine whether estimates of the effects of the independent variables in the model (here, TRDM) is invariant across the groups of interest (different levels of deviant peer exposure). While these models can be difficult to interpret, they can be combined with plotting interaction effects or the size of estimates across groups to aid understanding.

One approach to studying the interaction between an observed variable (deviant peer exposure) and a latent factor (understanding TRDM) is to multiply the observed variable with the latent factor score (see Figure 2). That is, rather than using the individual indicators of TRDM, TRDM and its interaction with deviant peer exposure will be measured using the inferred factor score, which is not directly observed. This approach estimates the latent factor as if it is an observed variable and can fail to correct parameter estimates for measurement error, much like non-latent approaches (Hancock & Mueller, 2013). The observed indicators of TRDM are internally consistent and load strongly onto a single factor, minimizing these risks. However, due to the limitations inherent to this approach, I propose the additional use of multigroup analyses with the aim of these two approaches working together to shed light on the processes at work. Additionally, multigroup analyses with more than two groups can provide evidence for non-linear interactions which the interaction models will not detect.

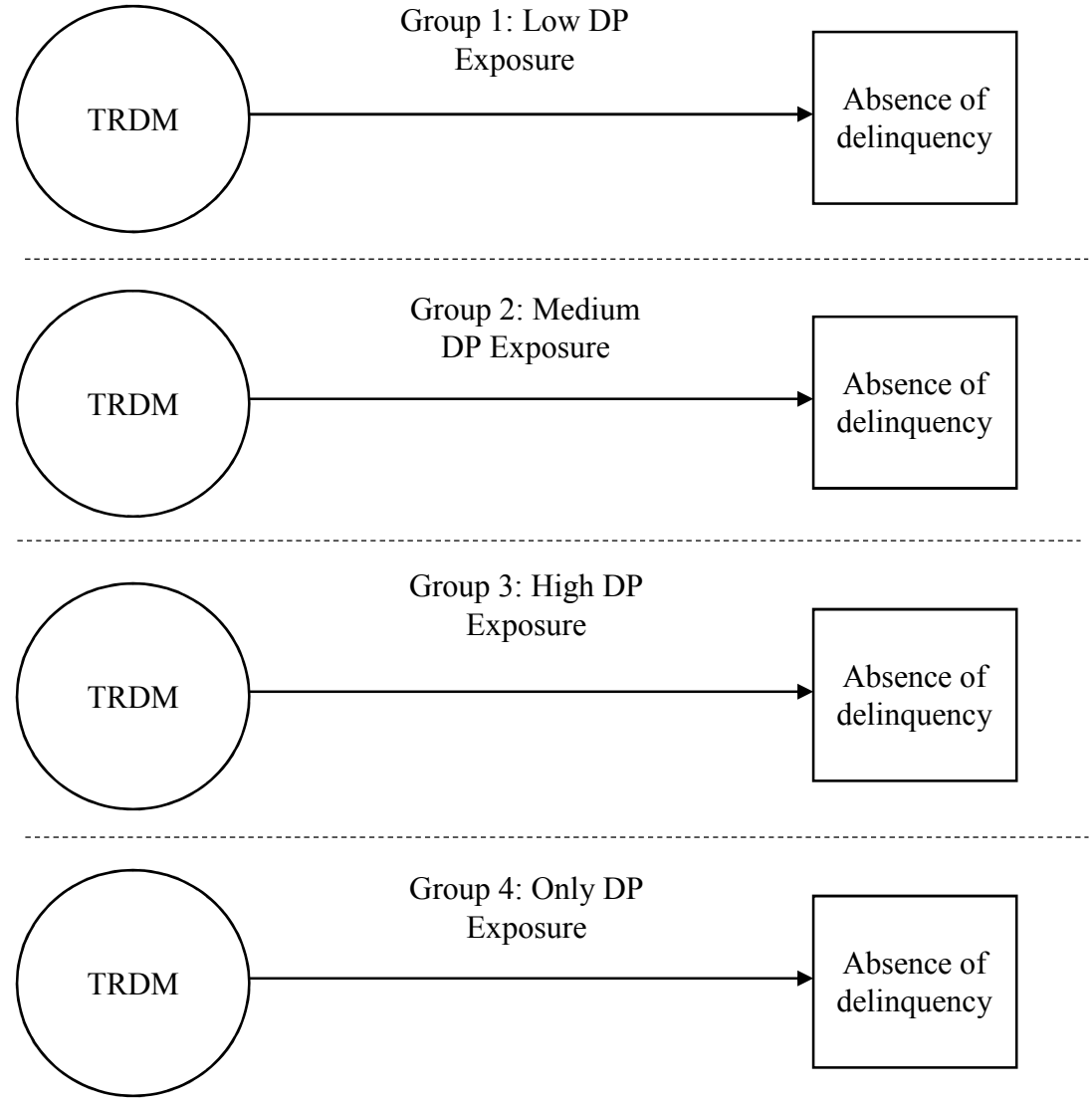
Figure 2. Measurement Model for Interaction Moderation Analyses



Deviant peer exposure, TRDM, and the interaction will be measured at Time 1. Resilience will be assessed at Time 3. Control variables are excluded from the figure.

Multigroup analyses test for differences in the impact of one independent variable (i.e., TRDM) between different groups of another variable (i.e., deviant peer exposure). In this approach, the statistical software estimates the model, with the grouping variable and the interaction omitted, once for each independent group (see Figure 3). This allows for comparison of parameter estimates, which can vary freely in each group, by examining the effect size and significance of the paths. This model is parsimonious and clear in its interpretation. However, a weakness of this approach is that it assumes one of the interacting variables is a single, observed categorical variable that can be used to form a relatively small number of groups, and the classification of these groups can be somewhat arbitrary (Hancock & Mueller, 2013).

Figure 3. Measurement Model for Multigroup Moderation Analyses



Estimated separately for each group of deviant peer exposure. Resilience assessed at Time 3. Control variables are excluded from the figure.

This approach is ideal for observed categorical variables (i.e. gender or race), but can be used if a relatively small number of theoretically-meaningful groups can be created from a continuous observed variable. I measure deviant peer exposure using a proportion representing how many of the adolescent's friends are delinquent. This relative operationalization is consistent with Sutherland's (1947) principle of

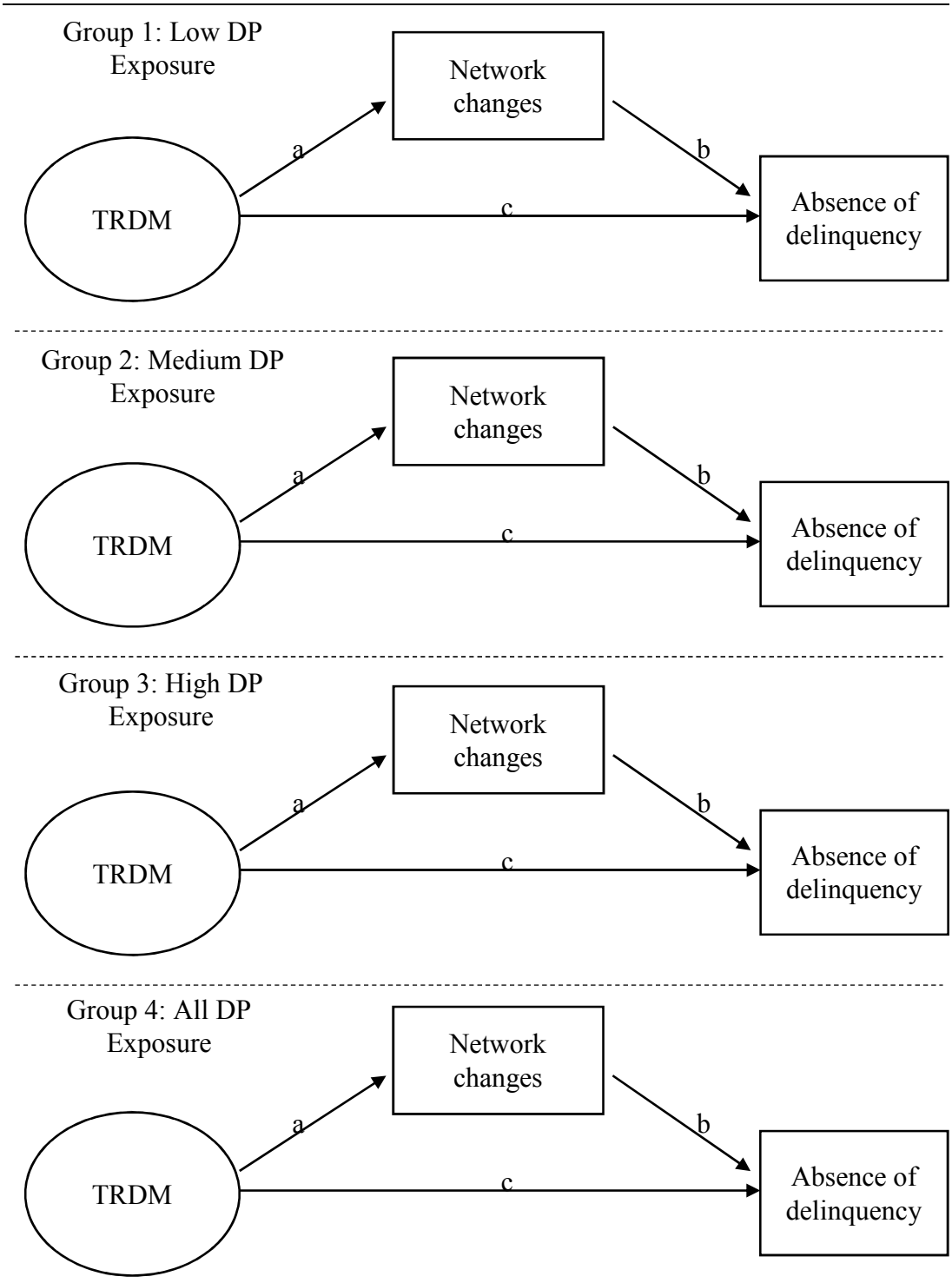
differential association, or the ratio of definitions favorable to those unfavorable to the commission of crime. Of particular interest is when delinquent associations *outweigh* non-delinquent associations – it is at this point where the theoretical "tipping point" should lie. If one's social network is completely non-deviant or completely deviant, there is the most consensus and least ambiguity on attitudes towards delinquency (Coleman, 1988; Granovetter, 1985). There should be less ambiguity when the friend group is mixed with less than half deviant (< 40% deviant, 33.13% of the sample), the most ambiguity when the friend group is split at about half (40-60% deviant, 33.20% of the sample)[19], some ambiguity when the deviance of the friend group exceeds half but is not completely deviant (>60% but not entirely deviant, 17.54% of the sample), and no ambiguity when the friend group is entirely deviant (100% deviant, 16.13% of the sample). Thus, for the multigroup analyses, I test whether the processes at hand differ according to these categories. This approach has the added benefit of assessing whether the impact of the moderation is non-linear – for example, if TRDM is most impactful for those with the most ambiguity (about 50% deviant network) and least impactful for those with the least ambiguity (100% deviant network), with effect sizes in between these for the other two groups, I would be able to observe these nonlinear differences between groups.

[19] This group could not be defined as exactly half (50%), because doing so would systematically exclude adolescents with an odd number of friends from membership in this category. The medium deviant peer exposure category was defined as a friend group that is 40-60% deviant for this reason. However, adolescents that have exactly 1 or 3 friends with deviance information still cannot fall in this category (and adolescents with only 1 friend can, by definition, only fall into the "all deviant" group or they will be excluded from the sample).

Moderated Mediation Analyses

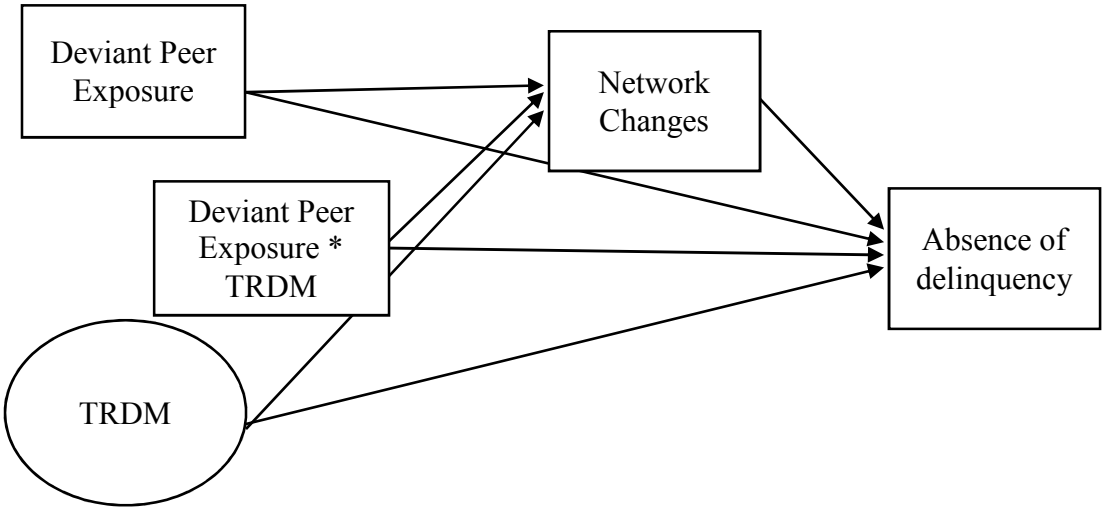
Mediation analysis, or process modeling, is typically used to identify the mechanisms by which one variable affects an outcome through one or more intermediary variables (Judd & Kenney, 1981). Using Baron and Kenney's (1986) framework for mediation, these analyses examine whether change in the deviance of adolescent's social network (at Time 2) partially or fully explains the impact of TRDM (at Time 1) on resilience (at Time 3). For example, referencing Figure 4 (the measurement model for multigroup moderated mediation analyses), the relationship can be said to be completely or totally mediated if paths a and b are significant and path c is no longer significant. The relationship shows signs of partial mediation if all three paths are significant, and path c changes in magnitude compared to before paths a and b were added (Figure 3). While this process will be more complex in the latent score moderated mediation analyses –involving the calculation of separate indirect effects of TRDM and its interaction with deviant peer exposure – the process will work the same (see Figure 5).

Figure 4. Measurement Model for Multigroup Moderated Mediation Analyses



Estimated separately for each group of deviant peer exposure. Resilience assessed at Time 3. Control variables are excluded from the figure.

Figure 5. Measurement Model for Interaction Moderated Mediation Analyses



Deviant peer exposure, TRDM, and the interaction will be measured at Time 1. Network changes will be measured at Time 2. Resilience assessed at Time 3. Control variables are excluded from the figure.

When the mediation process is thought to be dependent on one or more external variables (in this instance, dependent on the initial level of deviant peers), mediation and moderation are combined in order to examine their impact on the outcome of interest. This is referred to as conditional process modeling. Conditional process modeling avoids testing incomplete models by analyzing many processes simultaneously, acknowledging that some variable's (like TRDM) impact on an outcome (like resilience) may be mediated by another variable (like change in the deviance of one's social network) for some people and not others (for example, those with an initial high level of deviant peer exposure; see James & Brett, 1984). It is possible to use MPlus to test the mediating processes both using the multigroup analyses and latent factor score moderation. For both multigroup analyses and latent factor moderation models, I can calculate *conditional indirect effects* – or the effects

of one variable on another through an intermediary variables under certain conditions of a moderator variable (see Hayes & Preacher, 2013; Preacher et al., 2007). These analyses examine whether TRDM has an indirect impact on resilience through contributing to change in adolescents' friendship networks in the following wave with deviant peer exposure serving as the moderating variable. This indirect effect, if it exists, would likely be conditional on the initial degree of the adolescent's deviant peer exposure. If the size of the indirect effect differs by level of deviant peer exposure, that is evidence that the indirect effect is conditional.

Post-Estimation

As previously established, the goal of SEM is to confirm (or disconfirm) the model. It is thus necessary to estimate data model fit, comparing how the observed data fit with how the data should behave given the *a priori* specified theory. Measures of data-model fit compare how observed data match all the elements included in the model (including covariance, error, and disturbances). If the model fit is good, it means that the proposed variance and covariance resembles the observed covariances and variances in the data. A model with poor fit means that the data do not fit the hypothesized structure of the variables, and the specified relationships are likely not close to the data-generating processes in the environment.

There are a few different types of data model-fit indices, including absolute, parsimonious, and incremental fit indices. Absolute fit indices, such as the Standardized Root Mean Squared Residual (SRMR), examine the overall differences between the variances and covariances in the observed data and those specified in the model. These fit indices are sensitive to how many parameters are in the model, with

additional parameters improving the estimates. Parsimonious fit indices, such as the Root Mean Squared Error of Approximation (RMSEA), take into account the simplicity of the model, only improving when the parameters add useful information. Incremental fit indices, such as the Comparative Fit Index (CFI), evaluate a model's overall or parsimonious fit compared to another model, most commonly a null model (where the variables are completely unrelated). If the null model is rejected in favor of the specified model, it provides support for that model's fit.

There are no absolute values that determine whether a model should be retained or modified, but researchers have proposed guidelines for the SMSR, RMSEA, and CFI values to demonstrate good model fit. For example, some researchers suggest an RMSEA under .1, a SMSR below <.05, and a CFI of at least .90 (Browne & Cudeck, 1993; Kline, 2011; Steiger, 1990). Hu and Bentler (1999) conducted a simulation study examining the fit indices across models known to be correct or misspecified; based on their findings, they recommend an RMSEA of .06 or less, a SMSR of .08 or less, and a CFI of .95 or greater. However, this study was done using ML estimation, and may not generalize to other estimators. There is some evidence to suggest that weighted least-squares models should be held to a more stringent standard (Nye & Drasgow, 2011; Xia & Yang, 2019).

There is no "gold standard" fit index and no "gold standard" cut-off point. Examining model fit thus requires some degree of researcher interpretation. In addition, fit indices do not confirm whether the model has theoretical or predictive meaning (Kline, 2011). Even with indices showing good model fit, the model cannot be "confirmed" or "proven" true. Instead, it suggests that these indices could not

disconfirm the model and the model may be one explanation for the covariances and variances in the observed data. If the model displays poor fit, it is necessary to rely on theory to make model revisions and compare to look for improvements to model fit.

CHAPTER 4: RESULTS

For the results, I first examine the existence of a "resilient" group and differences in the sample by level of deviant peer exposure and level of resilience. I then present my models testing the impact of TRDM on resilience, including whether it varies according to the level of deviant peer exposure and whether TRDM is indirectly associated with resilience through prompting changes to the deviance of one's friends. Lastly, I conduct sensitivity analyses to test the robustness of my findings and summarize my results.

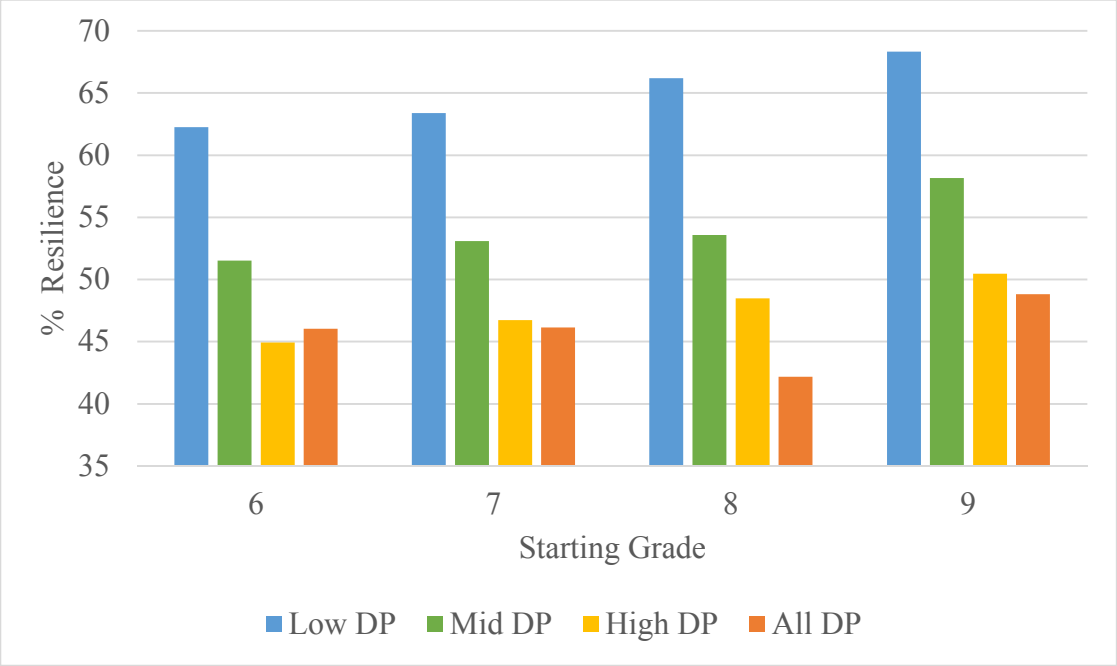
Descriptive Statistics

Averaging across all waves and all levels of deviant peer exposure, 53.15% of the sample demonstrated resilience (defined here as the absence of all deviance measured two waves in the future) despite exposure to deviant peers.[20] Figure 6 shows how resilience changed across waves and across levels of deviant peer influence, with the least resilience amongst younger adolescents exposed to a high or entirely deviant friend group. As adolescents are exposed to more deviant peers, the proportion that display resilience decreases. Across waves, the 65% resilience among those with low deviant peer exposure reduces to 46% amongst those with all deviant friends (see Table 4). One exception is the proportion of resilience amongst those with high and all deviant peers; those with all deviant peers have a similar level of

[20] Resilience refers to the absence of the 9 measured delinquency items. As deviance at this age is common and considered normal by many (see Moffit, 1993), my focus is on delinquency that can be seen as more serious and has the potential to lead to altered life circumstances. As such, I did exclude some less serious items that are at least deviant if not delinquent – such as alcohol use, smoking, and skipping school. Though this is appropriate for the focus of my dissertation, this could explain why the rates of resilience seem high, with on average over half of the sample displaying resilience.

resilience to those with high deviant peers at all waves besides 8th-10th grade, where the proportion of resilience noticeably dips. Adolescents in later grades demonstrated slightly more resilience, from an average of about 55% resilience from 6th – 8th grade compared to 59% from 9th – 11th grade (see Table 2). Consistent with findings that adolescents are most vulnerable to peer influence during younger adolescence (Steinberg & Monahan, 2007), resilience is most common when adolescents are in 11th grade (around 16-17 years of age).

Figure 6. Resilience Across Waves and Level of Deviant Peer Exposure



DP refers to deviant peers.

Pooled descriptive statistics according to level of deviant peer exposure can be found in Table 4. From a descriptive examination of how the variables change according to level of deviant peer exposure, TRDM tends to be lowest for those with a higher proportion of deviant peers. Those with more deviant peer exposure also are more likely to have been deviant in the past year, to be male, to be non-white, to have

lower socioeconomic status (as seen through free or reduced-price lunch), to have less parental monitoring and worse parental relations, and to be more impulsive. The relationships between deviant peer exposure and unstructured, unsupervised socializing (UUS) and number of friendship nominations appear nonlinear, both peaking for those with high exposure to deviant peers (60-99% deviant friend group).

Table 4. Pooled Sample Descriptive Statistics across Levels of Deviant Peer Exposure

	Low DP		*Mid DP*		*High DP*		*All DP*	
	Mean or %	SD	Mean or %	SD	Mean or %	SD	Mean or %	SD
No Delinquency [a]	64.79%	--	53.98%	--	47.91%	--	45.78%	--
Δ DP Proportion [b]	.10	.28	-.02	.30	-.16	.30	-.39	.34
DP Proportion	.25	.07	.50	.06	.73	.06	1.00	.00
TRDM	.17	.90	-.03	.95	-.15	.98	-.24	1.01
Prior deviance	30.36%	--	43.56%	--	56.42%	--	60.71%	--
Male	36.29%	--	50.74%	--	60.24%	--	65.23%	--
White	89.01%	--	85.22%	--	83.14%	--	79.40%	--
Free Lunch	-.52	1.53	-.20	1.65	-.10	1.66	.27	1.68
Parental Monitoring	4.42	.65	4.25	.74	4.14	.79	4.05	.83
Parent Relations	.02	.40	-.05	.42	-.11	.42	-.13	.45
Impulsivity	2.46	1.22	2.67	1.24	2.81	1.25	2.89	1.29
UUS	7.06	2.93	7.12	2.92	7.48	2.87	6.79	2.95
# Nominations	5.81	1.35	5.32	1.69	5.49	1.39	3.13	1.78
Tx Condition	45.35%	--	41.92%	--	40.81%	--	39.27%	--

N(%)	9,092 (34.36%)	8,815 (33.31%)	4,778 (18.05%)	3,779 (14.28%)

DP refers to Deviant Peers. UUS refers to unsupervised, unstructured socializing. Δ signifies change. [a] Measured at Time 3. [b]Measured at Time 2.

Turning attention to bivariate tests of differences between adolescents who displayed resilience at the starting wave (6th-8th grade) and those who do not (see Table 5)[21], I find that average TRDM is higher amongst those who display resilience, consistent with expectations. Those who show resilience tend to have a lower level of deviance amongst their friend group, also consistent with what researchers have found regarding peer influence. The average change in the deviance of the friend group tends to go down for both groups (which is unsurprising because adolescents had to have deviant friends at the starting wave to be included in the sample but can have no deviant friends at the next wave), with a slightly bigger drop for those who are "resilient." Adolescents who display resilience are also less likely to have engaged in prior deviance, to be male, to be non-white, and to have free or reduced-price lunch. They tend to have more parental monitoring, better parental relations, less impulsivity, and engage in less UUS. "Resilient" adolescents also have slightly more friends and are slightly more likely have been in the treatment group for the PROSPER intervention. Overall, the differences in independent and control variables observed between "resilient" versus "non-resilient" adolescents are in the expected directions.

[21] I here isolate the sample to the starting wave to allow me to conduct independent sample t-test and Chi-square tests, since the pooled sample could lead to the same individuals being categorized as displaying "Resilience" or "No Resilience" in different waves. Descriptive statistics for adolescents by resilience for the pooled sample are available in Appendix A.

Table 5. Descriptive Statistics by Resilience at Starting Wave (6th – 8th grade)

	Resilience		*No Resilience*	
	Mean or %	SD	Mean or %	SD
Δ DP Proportion[b] **	-.04	.32	-.01	.34
DP Proportion***	.43	.24	.50	.25
TRDM***	.30	.87	-.12	.95
Prior deviance***	19.82%	--	53.64%	--
Male***	46.41%	--	58.85%	--
White**	89.62%	--	86.33%	--
Free Lunch***	-.48	1.59	-.17	1.68
Parental Monitoring***	4.60	.55	4.32	.69
Parent Relations***	.16	.35	.02	.40
Impulsivity***	2.40	1.37	2.69	1.30
UUS***	6.94	3.24	7.33	3.13
# of Nominations***	5.51	1.69	5.33	1.74
Tx Condition**	47.17%	--	43.00%	--
N (%)	2,506 (54.82%)		2,065 (45.18%)	

DP refers to Deviant Peers. UUS refers to unsupervised, unstructured socializing. Δ signifies change.
[b] Measured at Time 2. † p < .10 * p < .05 ** p < .01 *** = p < .000 in a t-test or Chi-square test between the sample that displays resilience at Wave 7 (11th grade) and those who do not.

Analytic Models

Direct Effect of TRDM on Resilience to Deviant Peer Influence

In multivariate[22] structural equation models including an interaction between TRDM and the continuous measure of deviant peer exposure (Table 6), a higher proportion of deviance among the friend group is negatively associated with resilience across all waves. TRDM is, in accordance with Hypothesis 1, positively associated with resilience across all waves. However, the interaction between TRDM and deviant peer proportion is not statistically significant and switches signs, demonstrating no support for hypothesis 2a.

[22] Estimates of the effect of control variables are omitted from all Tables to allow for parsimonious interpretation of findings. In most models, control variables' associations with resilience remain in expected directions (see Table 5), though they are not always statistically significant.

Table 6. Direct Effect of TRDM on Resilience in Interaction Models

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DP Prop	-.29**	.11	-.32***	.09	-.32**	.10	-.24**	.08
TRDM	.12**	.03	.09***	.03	.12***	.02	.05*	.02
TRDM * DP	-.05	.09	-.04	.07	.00	.09	.07	.09
N	5,249		6,367		6,626		6,165	
χ^2	46.07***		14.06***		17.14***		27.03***	
RMSEA	.09		.05		.05		.07	
CFI	.97		.99		.99		.98	
SRMR	.02		.01		.01		.01	

DP refers to Deviant Peers. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

In these models, the control variables act in predicted directions (see Table B1 in Appendix B). Prior deviance is consistently negatively associated with resilience. Being male, of lower socioeconomic status, impulsive, and engaging in more unstructured, supervised socializing tends to be associated with a lower likelihood of displaying resilience. Parental monitoring is consistently associated with an increased likelihood of resilience, but parental relations only holds a significant positive effect from 8^{th} – 10^{th} grade. Being in the treatment condition was associated with a significant increase in resilience from 6^{th} – 8^{th} grade. Across all indicators, model fit is acceptable, though RMSEA does slightly exceed Hu and Bentler's (1999) more stringent threshold in the first and last waves.

In multigroup structural equation models (Table 7), TRDM is positively associated with resilience; however, the impact of TRDM on resilience appears mostly indistinguishable from null in the last wave from $9^{th} – 11^{th}$ grade, with a marginally significant positive association with resilience for only those with high exposure to deviant peers. All significant (and nonsignificant) estimates of TRDM's association with resilience are positive, providing further support for TRDM acting as a promotive factor (Hypothesis 1) in all but the last wave.

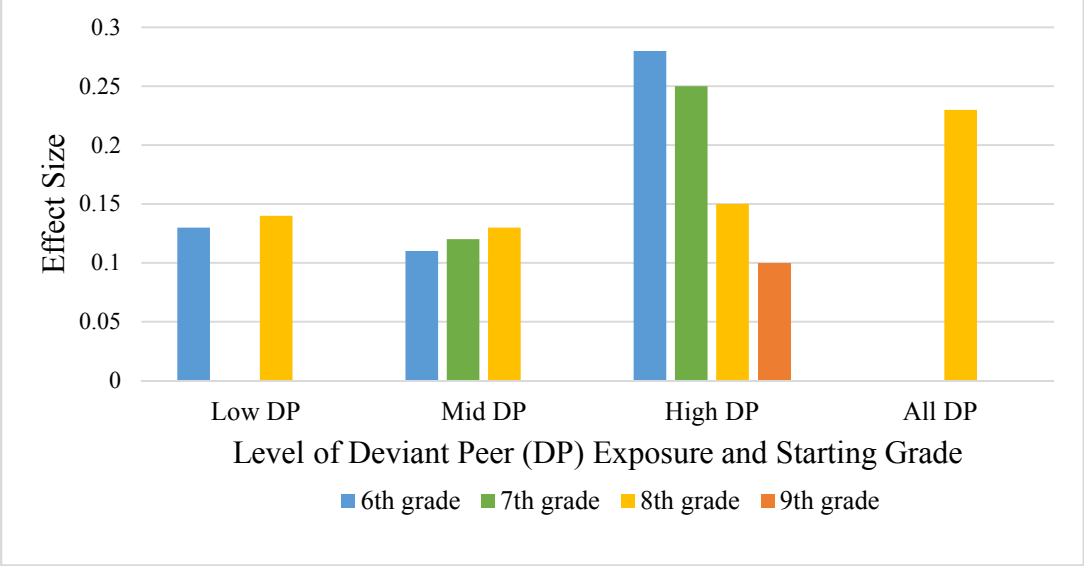
Table 7. Direct Effect of TRDM on Resilience in Multigroup Models

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
					CFI = .97;
TRDM	0.13*	.11†	.28***	.04	RMSEA = .03;
	(.06)	(.06)	(.07)	(.10)	SRMR = .07;
N	*2,278*	*1,794*	*692*	*559*	$\chi^2 = 414.37$***
$7^{th} – 9^{th}$					
					CFI = .97
TRDM	.03	.12**	.25**	.03	RMSEA = .03
	(.05)	(.04)	(.07)	(.07)	SRMR = .06
N	*2,366*	*2,199*	*1,131*	*738*	$\chi^2 = 440.10$***
$8^{th} – 10^{th}$					
					CFI = .97
TRDM	.14**	.13**	.15*	.23**	RMSEA = .03
	(.05)	(.05)	(.06)	(.07)	SRMR = .06
N	*2,122*	*2,247*	*1,415*	*1,004*	$\chi^2 = 475.98$***
$9^{th} – 11^{th}$					
					CFI = .97
TRDM	.08	.03	.10†	.01	RMSEA = .03
	(.05)	(.05)	(.05)	(.08)	SRMR = .07
N	*1,895*	*2,005*	*1,237*	*1,103*	$\chi^2 = 453.26$***

DP refers to Deviant Peers. † $p < .10$ * $p < .05$ ** $p < .01$ *** = $p < .000$. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Turning to Hypothesis 2b, the significance and magnitude of the association between TRDM and resilience varies by level of deviant peer exposure, with the largest and most consistent effect for those with high exposure to deviant peers. The magnitude of all significant (including marginally significant) effects can be seen in Figure 7. Comparing the effect sizes between level of deviant peer exposure provides evidence for a non-linear interaction between TRDM and proportion of deviant peers and mixed support for Hypothesis 2b. Specifically, TRDM appears to be especially protective when a high proportion – but not all – of the adolescents' peers are deviant. There is one exception: in the wave that starts in 8th grade, TRDM has the largest effect for those with all deviant peers. TRDM maintains a significant positive effect for adolescents with low or mid deviant peer exposure in all waves except the last.

Figure 7. ß of TRDM on Resilience by Grade and Exposure to Deviant Peers



Examining the equality of coefficients between groups of deviant peer exposure (Table 8), TRDM's coefficient for the group with high exposure does significantly differ from the group with all deviant peer exposure in 6th-8th – with

marginally significant differences from the groups with low and mid deviant peer exposure – and from those with low or all deviant peer exposure during grades 7th-9th, highlighting the strength of these differences at the earlier waves. Though the TRDM coefficient for those with all deviant peers is largest in magnitude from grades 8th – 10th, it does not significantly differ from the estimates at other levels of exposure. There are also no significant differences across groups from grades 9th-11th, though the estimate of TRDM's effect on resilience is only marginally significant at a high level of deviant peer exposure.

Table 8. Testing for Multigroup Differences in TRDM Direct Effect Estimates

	Low DP	Mid DP	High DP
6th – 8th			
Mid DP	.06	--	--
High DP	3.17†	3.72†	--
All DP	.61	.35	4.26*
7th – 9th			
Mid DP	2.00	--	--
High DP	6.32*	2.18	--
All DP	.00	1.14	4.47*
8th – 10th			
Mid DP	.03	--	--
High DP	.02	.08	--
All DP	1.05	1.42	.68
9th – 11th			

Mid DP	.50	--	--
High DP	.04	.82	--
All DP	.61	.06	.88

DP refers to Deviant Peers. † $p < .10$ * $p < .05$ ** $p < .01$ *** = $p < .000$ in a Wald χ^2 test of equality of coefficients.

The control variables in the multigroup models again act in predicted directions (see Table B2 in Appendix B), though not always significant across all levels of deviant peer exposure. Prior deviance is the most reliable predictor of resilience of the control variables, consistently associated with a lower likelihood of resilience amongst each wave and level of deviant peer exposure. Impulsivity is negatively associated with resilience and parental monitoring positively associated with resilience at most waves and levels of exposure. Being male and of lower socioeconomic status is negatively associated with resilience most commonly at low levels of deviant peer exposure. Being in the treatment condition was associated with a significant increase in resilience from 6^{th} – 8^{th} grade only at low and mid-levels of deviant peer exposure. Model fit remains good across the four models according to Hu and Bentler's (1999) standards.

Indirect Effect of TRDM on Resilience to Deviant Peer Influence

In interaction models testing for evidence of an indirect impact of TRDM on resilience (Table 9), higher levels of deviance among the friend group remains negatively associated with resilience across all waves, with larger estimates of its effect than in the models that only included direct effects. The change in deviant peers is also negatively and significantly associated with resilience, signifying that an

increase in the proportion of one's friend group that is deviant will further decrease the likelihood of resilience. TRDM continues to be, in accordance with Hypothesis 1, positively associated with resilience across all waves, and the magnitude of the effect for each wave is identical to that in the direct model. The interaction between TRDM and deviant peer proportion continues to not be statistically significant.

Table 9. Indirect Effect of TRDM on Resilience in Interaction Models

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DV: Δ DP Prop								
TRDM	.00	.01	-.02**	.00	-.00	.01	-.01	.01
TRDM*DP	.06***	.02	.05**	.00	.02	.02	-.01	.02
DV: Resilience								
Δ DP Prop	-.39***	.08	-.35***	.08	-.46***	.07	-.24**	.08
DP Prop	-.58***	.13	-.57***	.10	-.62***	.10	-.40***	.09
TRDM	.12***	.03	.09**	.03	.12***	.02	.05*	.02
Indirect Effect	-.00	.00	.01*	.00	.00	.00	.00	.00
Total Effect	.12**	.03	.09**	.03	.13***	.02	.05*	.02
TRDM*DP	-.03	.09	-.05	.06	.03	.09	-.08	.10
Indirect Effect	-.02**	.01	-.02*	.01	-.01	.01	.00	.00
Total Effect	-.05	.09	-.06	.06	.02	.09	-.07	.10
N	5,249		6,367		6,626		6,165	
χ^2	46.07***		4.36*		39.52***		92.55***	
RMSEA	.09		.02		.08		.12	
CFI	.98		.99		.98		.95	

SRMR	.01	.00	.01	.02

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

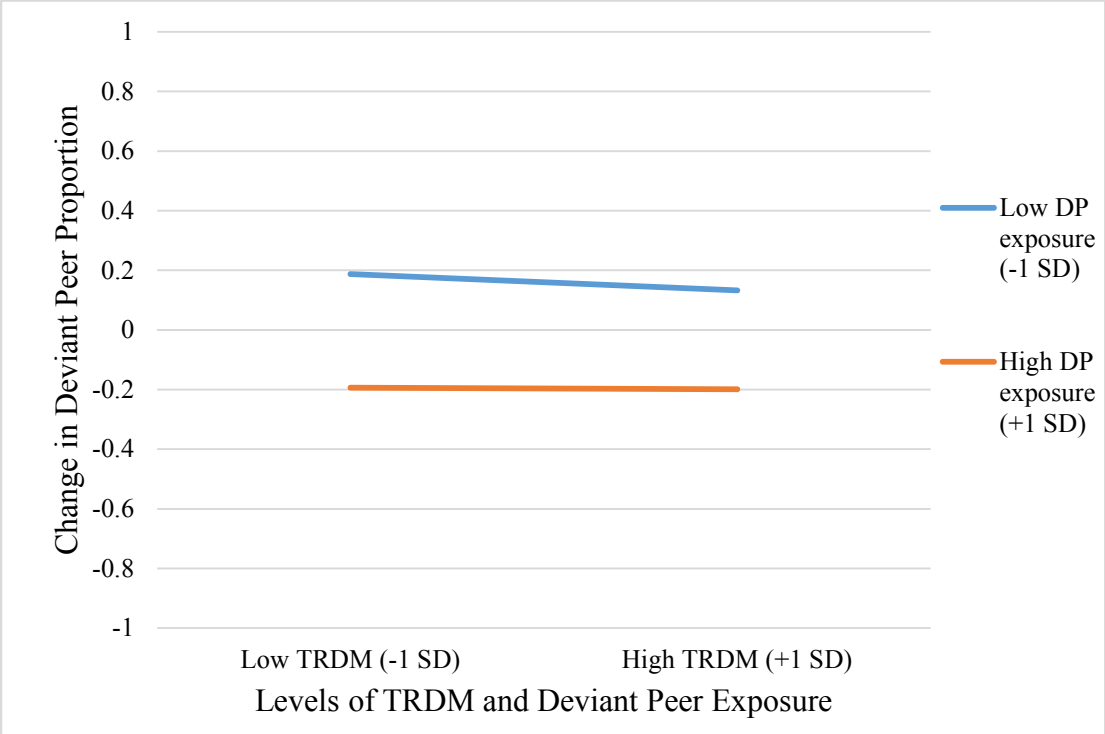
The total effect of TRDM on resilience remains positive at each wave with the addition of the indirect effects, and there is not much evidence for an indirect effect of TRDM. Though an increase in deviant peer proportion is negatively associated with resilience (supporting Hypothesis 3b), TRDM is only negatively associated with change in deviant peer proportion at the next wave for 7^{th} – 8^{th} grade, providing very limited support for Hypothesis 3a. TRDM's association with a decrease in deviant peer proportion from 7th-8th grade corresponded to a small increase in the likelihood of resilience at 9th grade, providing evidence of a small indirect effect from only 7^{th} – 9^{th} grade. The coefficients measuring TRDM's direct effect on resilience do not lose their statistical significance or become smaller in magnitude, one of the conditions that must be met to demonstrate mediation (Judd & Kenney, 1981). Thus, the interaction models do not support the contention that the positive effect of TRDM is partially or fully mediated by change in deviant peer proportion (Hypothesis 3).

There is some evidence of an indirect effect of the *interaction* between TRDM and deviant peer proportion at the first two waves, but this interaction is only interpretable from 7^{th}-8^{th} grade when TRDM is also a statistically significant predictor of change in deviant peer proportion[23]. In this wave, TRDM is only associated with a

[23] Deviant peer proportion is, though not listed in the table, significantly and negatively associated with a change in deviant peer proportion at the next wave in each model. This signifies an increased likelihood that those with a greater proportion of deviant peers have less deviance amongst their peers next year and likely represents a regression to the mean, as those with no deviant peers were removed from the analysis at the starting wave.

reduction in deviant peer proportion for those who do not already have a high proportion of deviant peers, though the magnitudes of both effects are small. Figure 8 shows the plot of this interaction: high TRDM (defined as 1 SD above the mean) is associated with a slight reduction in the proportion of deviant peers only for those who do not already have a high degree of deviant peers (defined as 1 SD above the mean, about 75%). However, the figure also demonstrates that this interaction is small in magnitude and has limited utility in its interpretation; for those with low exposure to deviant peers, even those with high TRDM still tended to increase the deviant proportion of the peer group at the next wave. Given that this interaction is only found in one year and substantively small, the models do not support moderated mediation, whereby the impact of TRDM is fully or partially mediated only at certain levels of deviant peer exposure.

Figure 8. Interaction between TRDM and Deviant Peer Proportion in 7th Grade Predicting Change in Deviant Peer Proportion in 8th Grade



The control variables maintain a similar impact on resilience as in the direct interaction models, and many are also significant predictors of change in deviant peer proportion at the next wave (see Table B2 in Appendix B). Prior deviance, lower socioeconomic status, impulsivity, engaging in unstructured, unsupervised socializing, and being male are associated with a significant increase in deviant peer proportion at the next wave. Parental monitoring is associated with a decrease in deviant peer proportion at the first two sets of waves, while parental relations are associated with a decrease at the last two sets of waves. Being in the treatment condition is associated with a lower proportion of deviant peers at the first (6^{th} -8^{th} grade) and last (9^{th} – 11^{th}) waves. Model fit is still acceptable, through RMSEA slightly exceeds most thresholds in all waves except that from 7^{th}-9^{th} (Browne & Cudeck, 1993; Hu & Bentler, 1999; Kline, 2011; Steiger, 1990).

The multigroup indirect models (Table 10) paint a more complex picture, but still do not provide evidence of a clear indirect pathway. TRDM continues to be positively associated with resilience. The largest and most consistent effects are still found for those with a high proportion of deviant peer exposure (but, curiously, not all deviant peers). Tests for equality of TRDM's coefficients between levels of deviant peer exposure (Table 11) produce similar results to the direct models; the effect of TRDM significantly differs from some other groups for those with high exposure at the earlier waves (6^{th} – 9^{th} grade).

Table 10. Indirect Effect of TRDM on Resilience in Multigroup Models

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} - 8^{th}$					
	On Δ DP Prop				
TRDM	-.01	.03*	.01	.03	
	(.01)	(.01)	(.02)	(.02)	
	On Resilience				
Δ DP Prop	-.47**	-.26*	-.40*	-.22	CFI = .97
	(.14)	(.12)	(.18)	(.17)	RMSEA = .03
TRDM	.12*	.12†	.28***	.05	SRMR = .06
	(.05)	(.06)	(.07)	(.10)	χ^2 = 432.68***
Indirect Effect	.01	-.01	-.00	-.01	
	(.01)	(.00)	(.01)	(.01)	
Total Effect	.13*	.11†	.28***	.04	
	(.06)	(.06)	(.07)	(.01)	
N	*2,278*	*1,794*	*692*	*559*	
$7^{th} - 9^{th}$					
	On Δ DP Prop				
TRDM	-.04***	-.02	-.01	.02	
	(.01)	(.01)	(.01)	(.02)	
	On Resilience				CFI = .97
Δ DP Prop	-.38**	-.30*	-.54**	.03	RMSEA = .02
	(.12)	(.13)	(.17)	(.20)	SRMR = .05
TRDM	.02	.12*	.24**	.03	χ^2 = 458.34***
	(.05)	(.05)	(.07)	(.07)	
Indirect Effect	.01*	.01	.01	-.00	
	(.00)	(.00)	(.00)	(.00)	
Total Effect	.03	.12**	.25**	.03	
	(.05)	(.04)	(.07)	(.07)	
N	*2,366*	*2,199*	*1,131*	*738*	
$8^{th} - 10^{th}$					
	On Δ DP Prop				
TRDM	-.00	-.02†	.03*	-.03	CFI = .97
	(.01)	(.01)	(.01)	(.02)	

	On Resilience				RMSEA = .03
Δ DP Prop	-.57***	-.31*	-.45***	-.48**	SRMR = .05
	(.12)	(.14)	(.12)	(.15)	χ^2 = 494.34***
TRDM	.14*	.12*	.16**	.21**	
	(.05)	(.05)	(.06)	(.07)	
Indirect Effect	.00	.01	-.02*	.01	
	(.01)	(.00)	(.01)	(.01)	
Total Effect	.14**	.13**	.15*	.23**	
	(.05)	(.05)	(.06)	(.07)	
N	*2,123*	*2,248*	*1,417*	*1,006*	
$9^{th} – 11^{th}$					
	On Δ DP Prop				
TRDM	-.00	.00	-.00	-.04*	
	(.01)	(.01)	(.02)	(.02)	CFI = .96
	On Resilience				RMSEA = .03
Δ DP Prop	-.26†	-.13	-.29*	-.26	SRMR = .06
	(.14)	(.13)	(.14)	(.22)	χ^2 = 470.36***
TRDM	.08	.03	.10†	.00	
	(.05)	(.05)	(.05)	(.07)	
Indirect Effect	-.00	-.00	-.00	.01	
	(.00)	(.00)	(.00)	(.01)	
Total Effect	.08	.03	.10†	.01	
	(.05)	(.05)	(.05)	(.08)	
N	*1,895*	*2,005*	*1,237*	*1,103*	

DP refers to Deviant Peers. Δ signifies change. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 11. Testing for Multigroup Differences in TRDM Total Effect Estimates

	Low DP	Mid DP	High DP
$6^{th} – 8^{th}$			
Mid DP	.06	--	--
High DP	3.15†	3.71†	--
All DP	.61	.35	4.25*

$7^{th} – 9^{th}$			
Mid DP	2.00	--	--
High DP	6.34*	2.19	--
All DP	.00	1.14	4.49*
$8^{th} – 10^{th}$			
Mid DP	.03	--	--
High DP	.02	.08	--
All DP	1.06	1.43	.68
$9^{th} – 11^{th}$			
Mid DP	.50	--	--
High DP	.04	.81	--
All DP	.61	.06	.87

DP refers to Deviant Peers. † $p < .10$ * $p < .05$ ** $p < .01$ *** = $p < .000$ in a Wald χ^2 test of equality of coefficients.

Although there are some signs of a possible indirect relationship between TRDM and resilience through change to their deviant networks, the direction and significance of these effects vary. For 7^{th} graders with a low level of deviant peer exposure and 9^{th} graders with an entirely deviant peer group, higher TRDM amongst those with a low level of deviant peer exposure was associated with a decrease in the deviant proportion of one's peer group at the next wave, consistent with Hypothesis 3a. Yet, among 6^{th} graders with mid-level exposure and 8^{th} graders with high exposure to deviant peers, higher TRDM was associated with an *increase* in the deviant peer proportion at the next wave. Thus, the findings regarding Hypothesis 3a are inconsistent and do not provide compelling support.

Testing Hypothesis 3b, the effect of an increase in deviant peer proportion on resilience is consistently negative, but not found amongst all waves and all types of deviant peer groups. Among 6th and 7th graders, an increase in deviant peer proportion is associated with a decrease in resilience for all except adolescents with entirely deviant peers. For 8th graders, that negative effect is extended to those with all deviant peers (signifying here that a *decrease* in deviant peer exposure is associated with an *increase* in resilience). In 9th graders, this association is only found for those with low or high exposure to deviant peers.

Given the mixed finding regarding Hypotheses 3a and 3b, it is unsurprising that the presence and direction of an indirect effect of TRDM through changing social networks is unclear. There is no evidence of an indirect effect for multigroup models starting at grade 6 and grade 9 (see Table 10). For 7th graders with low exposure to deviant peers, there is a small positive indirect effect, whereby higher TRDM is associated with an increased likelihood of resilience through prompting a prosocial change to adolescents' friend groups. However, for 8th graders with a high level of exposure, higher TRDM has a negative indirect effect on resilience. This indicates that, among those with mostly deviant peers, higher TRDM is associated with a slight decrease in the likelihood of resilience due to an increase in the deviance of one's friends at the next wave, though the total effect of TRDM on resilience remains positive. The remaining indirect effects do not significantly differ from null. Additionally, the direct estimates of TRDM remain very similar to those found in the models in Table 7 and do not show consistent evidence of being reduced in magnitude or losing their statistical significance. Overall, the multigroup models are

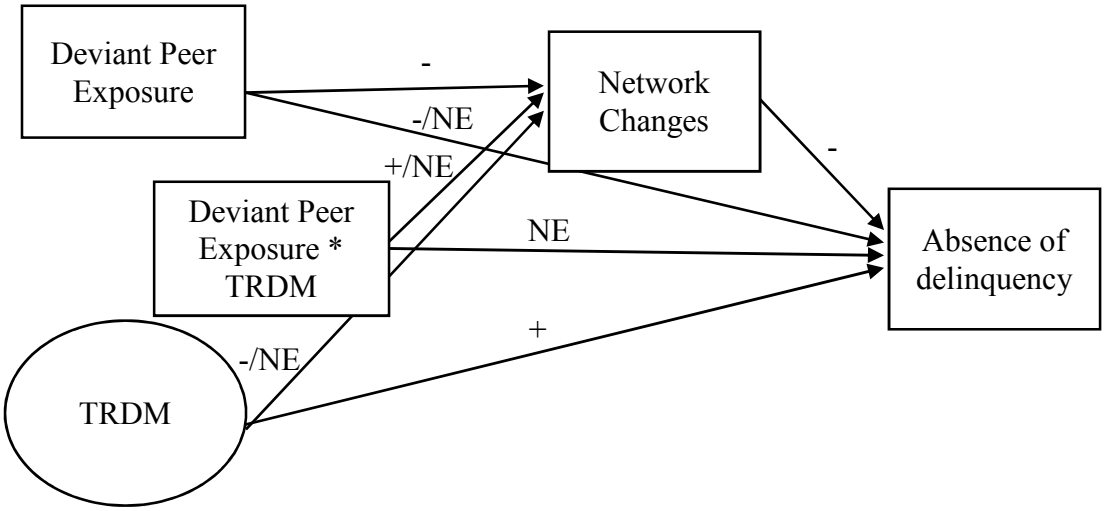
not supportive of an indirect path of TRDM through change in the deviance of one's friend groups, providing evidence against Hypothesis 3.

The control variables for the indirect multigroup models maintain a similar impact on resilience as in the direct models; the control variables also significantly predict change in deviant peer proportion among some levels of deviant peer exposure and waves (see Table B3, Appendix B). Prior deviance, lower socioeconomic status, and being male are associated with an increase in deviant peer proportion across most waves and levels of deviant peer exposure. Parental monitoring is associated with a lower proportion of deviant peers for some groups and waves, while unstructured, unsupervised socializing and impulsivity are associated with an increase in deviant peer proportion for some groups and waves. Being white appears to increase deviant peer proportion for those with high deviant peer exposure for the 6^{th}-7^{th} graders but decrease the deviant peer proportion for those with low or mid-level deviant peer exposure in 7^{th} – 8^{th} grade. Being in the treatment group was associated with a decrease in deviant peer group across all levels of deviant peer exposure for the 6^{th} – 7^{th} graders and amongst 9^{th} – 10^{th} graders with low or mid-level deviant peer exposure. There were no large changes to model fit compared to the direct multigroup models, with indices still well within acceptable ranges.

Figures 9 and 10 show a summary of the overall findings from the interaction and multigroup structural equation models, respectively. TRDM is associated with an increase in resilience across waves, and this effect is most consistent and largest in magnitude amongst those with a high level of deviant peer exposure. Deviant peer

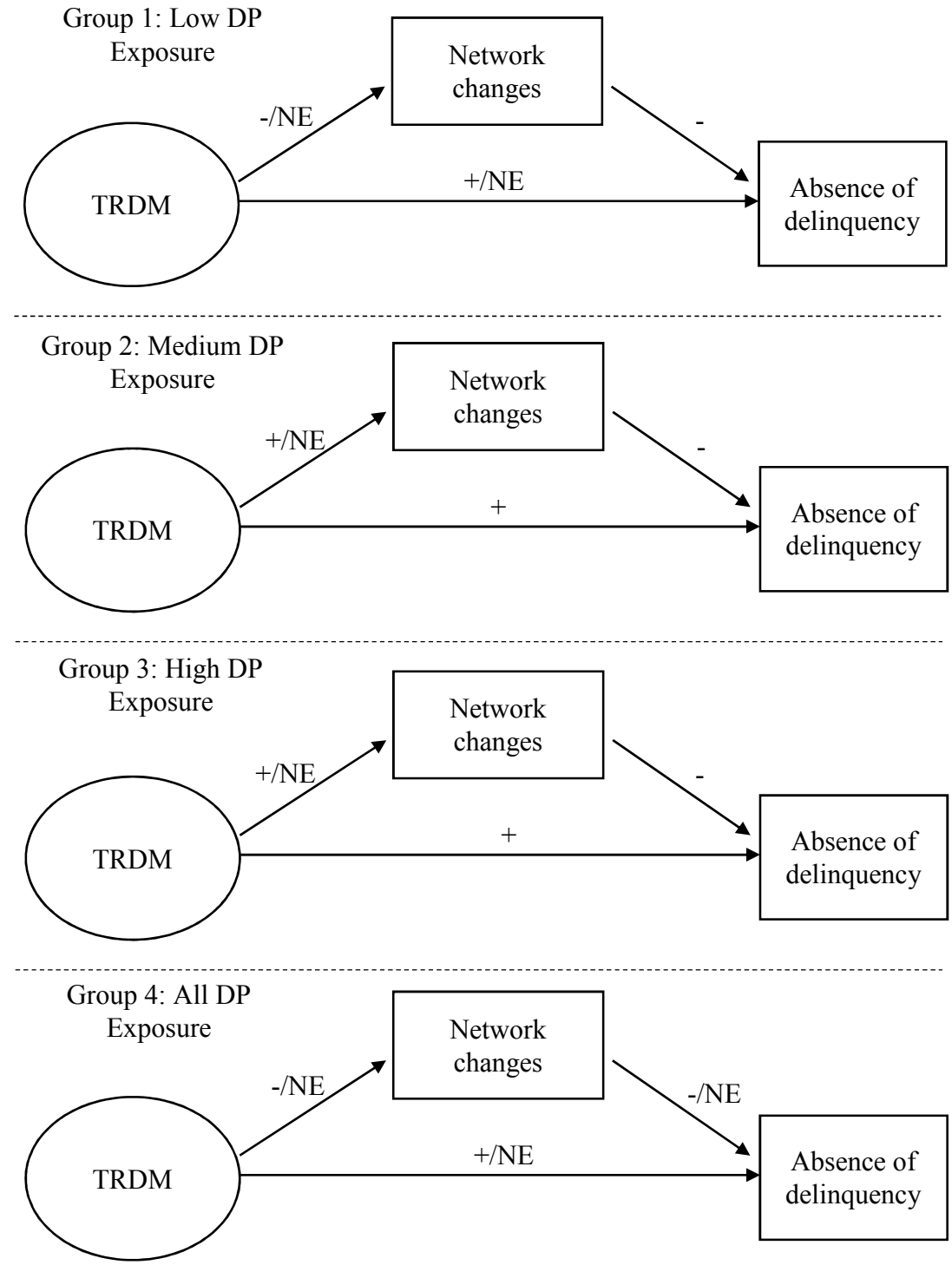
exposure at the starting wave and an increase in deviant peer exposure at the next wave have a negative impact on resilience. These models do not provide reliable evidence that TRDM has an indirect effect on resilience through prompting a positive change to adolescents' social networks.

Figure 9. Summary of Interaction Analyses



NE refers to no effect.

Figure 10. Summary of Multigroup Analyses



DP refers to Deviant Peers. NE refers to no effect.

Sensitivity Analyses

Omitting Lagged Dependent Variable Control

One criticism of research on deviant peer influence that include lagged measures of the dependent variable (LDV's) is that this is "too strong" of a control for peer selection, leading researchers to underestimate peer influence (McGloin & Thomas, 2019). As I control for prior deviance (the inverse of resilience) in my main models, I conduct sensitivity analyses omitting this LDV to estimate an "upper bound" of the effects of peer socialization (see Haynie & Osgood, 2005).

In accordance with predictions, removing prior deviance from the model does lead to larger estimates of the negative association between deviant peer influence and resilience (see Table 12). Removing the LDVs from both the multigroup and interaction models does also lead to small gains in the magnitude and statistical significance of TRDM's direct effect on resilience (see also Table 13) but does not change the substantive conclusions of the findings. The indirect models act in a similar fashion: although the magnitude and significance of the coefficients grow, I draw similar conclusions from the models both with and without prior deviance (see Tables 14 and 15). The exception to this is the multigroup models during 9^{th} – 11^{th} grade (Tables 13 and 15), which did not find TRDM to be consistently significant; in the models without prior deviance, TRDM is associated with increased resilience for those with low, medium, or high proportions of deviant peers (but not for those with all deviant peers). The true magnitude and significance of the effect of TRDM and deviance of the peer group likely lies somewhere between the estimates with and without the LDVs (Haynie & Osgood, 2005).

Table 12. Direct Effect of TRDM on Resilience in Interaction Models without Lagged Dependent Variable

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DP Prop	-.40***	.10	-.44***	.09	-.50***	.09	-.44***	.08
TRDM	.18***	.03	.15***	.02	.17***	.02	.09***	.02
TRDM * DP	.03	.09	-.01	.06	-.02	.10	-.07	.08
N	5,251		6,375		6,630		6,168	
χ^2	49.00***		14.90***		15.77***		26.13***	
RMSEA	.10		.05		.05		.06	
CFI	.97		.99		.99		.98	
SRMR	.02		.01		.01		.01	

DP refers to Deviant Peers. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 13. Direct Effect of TRDM on Resilience in Multigroup Models without Lagged Dependent Variable

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
TRDM	.17** (.05)	.19** (.06)	.35*** (.06)	.18† (.10)	CFI = .97; RMSEA = .03; SRMR = .07;
N	*2,278*	*1,796*	*692*	*559*	χ^2 = 397.24***
$7^{th} – 9^{th}$					
TRDM	.09* (.04)	.19*** (.04)	.30*** (.07)	.10 (.07)	CFI = .97 RMSEA = .03 SRMR = .06
N	*2,370*	*2,202*	*1,132*	*738*	χ^2 = 422.73***
$8^{th} – 10^{th}$					
TRDM	.19** (.05)	.18*** (.05)	.19** (.06)	.29*** (.07)	CFI = .97 RMSEA = .03 SRMR = .07

N	*2,123*	*2,249*	*1,415*	*1,006*	χ^2 = 454.34***
$9^{th} - 11^{th}$					
					CFI = .96
TRDM	.10*	.10*	.15**	.07	RMSEA = .03
	(.05)	(.05)	(.06)	(.07)	SRMR = .07
N	*1,896*	*2,005*	*1,239*	*1,103*	χ^2 = 446.18***

DP refers to Deviant Peers. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 14. Indirect Effect of TRDM on Resilience in Interaction Models without Lagged Dependent Variable

	6^{th}-8^{th}		*7^{th}-9^{th}*		*$8^{th} - 10^{th}$*		*9^{th}- 11^{th}*	
	ß	SE	ß	SE	ß	SE	ß	SE
DV: Δ DP Prop								
TRDM	.00	.01	-.02***	.00	.01	.01	.01	.01
TRDM*DP	.05**	.02	.05**	.02	-.02	.02	.01	.02
DV: Resilience								
Δ DP Prop	-.45***	.07	-.42***	.07	-.54***	.07	-.33***	.07
DP Prop	-.75***	.12	-.73***	.10	-.84***	.10	-.65***	.09
TRDM	.18***	.03	.14***	.03	.16***	.02	.09***	.02
Indirect Effect	-.00	.00	.01*	.00	.00	.00	.00	.00
Total Effect	.16***	.03	.14***	.02	.17***	.02	.09***	.02
TRDM*DP	.05	.09	-.04	.06	.02	.09	-.04	.09
Indirect Effect	-.01**	.00	-.02*	.01	-.01	.01	.00	.01
Total Effect	.01	.02	-.06	.06	.01	.10	-.04	.09
N	5,251		6,375		6,630		6,168	
χ^2	49.00***		4.36*		37.95***		90.72***	

RMSEA	.10	.02	.08	.12
CFI	.98	.99	.98	.94
SRMR	.01	.00	.01	.02

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 15. Indirect Effect of TRDM on Resilience in Multigroup Models without Lagged Dependent Variable

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
	On Δ DP Prop				
TRDM	-.02	.02†	.00	.03	
	(.01)	(.01)	(.02)	(.02)	
	On Resilience				
Δ DP Prop	-.52***	-.32**	-.43**	-.30*	CFI = .97
	(.13)	(.11)	(.17)	(.14)	RMSEA = .03
TRDM	.16**	.20**	.35***	.18*	SRMR = .06
	(.05)	(.06)	(.06)	(.09)	χ^2 = 414.92***
Indirect Effect	.01	-.01	-.00	-.01	
	(.00)	(.00)	(.01)	(.01)	
Total Effect	.13**	.16**	.33***	.16†	
	(.04)	(.05)	(.06)	(.01)	
N	*2,278*	*1,796*	*692*	*559*	
$7^{th} – 9^{th}$					
	On Δ DP Prop				CFI = .97
TRDM	-.04***	-.02*	-.02†	.01	RMSEA = .03
	(.01)	(.01)	(.01)	(.02)	SRMR = .06
	On Resilience				χ^2 = 441.08***
Δ DP Prop	-.40**	-.40**	-.58***	-.10	
	(.11)	(.12)	(.17)	(.18)	

TRDM	.07†	.18***	.29***	.10	
	(.04)	(.04)	(.07)	(.07)	
Indirect Effect	.02**	.01†	.01	-.00	
	(.01)	(.01)	(.01)	(.00)	
Total Effect	.09*	.19***	.30***	.10	
	(.04)	(.04)	(.07)	(.07)	
N	*2,370*	*2,202*	*1,132*	*738*	
$8^{th} - 10^{th}$					
	On Δ DP Prop				
TRDM	-.01	-.02*	.03†	-.03†	
	(.01)	(.01)	(.01)	(.02)	
	On Resilience				
Δ DP Prop	-.65***	-.37**	-.57***	-.53***	CFI = .97
	(.12)	(.12)	(.12)	(.14)	RMSEA =
TRDM	.18**	.18***	.20**	.27***	.03
	(.06)	(.05)	(.06)	(.07)	SRMR = .06
Indirect Effect	.01	.01†	-.02†	.02	χ^2 =
	(.01)	(.00)	(.01)	(.01)	473.27***
Total Effect	.19**	.18***	.19**	.28***	
	(.05)	(.05)	(.06)	(.07)	
N	*2,124*	*2,250*	*1,417*	*1,008*	
$9^{th} - 11^{th}$					
	On Δ DP Prop				
TRDM	-.00	-.00	-.00	-.04*	
	(.01)	(.01)	(.02)	(.02)	CFI = .96
	On Resilience				RMSEA =
Δ DP Prop	-.36**	-.26*	-.29*	-.32	.03
	(.13)	(.12)	(.13)	(.22)	SRMR = .06
TRDM	.10*	.10*	.15**	.06	χ^2 =
	(.05)	(.05)	(.06)	(.07)	470.36***
Indirect Effect	-.00	-.00	-.00	.01	
	(.00)	(.00)	(.00)	(.01)	
Total Effect	.08	.03	.10†	.01	
	(.05)	(.05)	(.05)	(.08)	
N	*1,896*	*2,005*	*1,239*	*1,103*	

DP refers to Deviant Peers. Δ signifies change. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Accounting for Criminal Justice System Involvement

It may not just be prior engagement in deviance that predicts its continuation, but also whether or not that prior engagement has been dealt with in a formal manner. Labeling theory hypothesizes that formal interaction with the criminal justice system will change others' perceptions of the deviant, knife the deviant off from conventional opportunities and networks, and alter the deviant's own self-concept, eventually resulting in further deviance (Lemert, 1951; Becker, 1963). A wide body of literature now supports the premise that individuals experience institutional and interpersonal exclusion after criminal justice system involvement (Bernburg & Krohn, 2003; Bernburg et al., 2006; Jacobsen, 2020; Widdowson et al., 2016; Wiley et al., 2013). Not controlling for these experiences could mask the impact of TRDM on the later deviant composition of one's friendship group and resilience. Those who have been arrested are more likely both to have deviant peer groups and to reoffend in the future (Bernburg et al., 2006). Thus, if TRDM is not promotive or protective in a such a way as to overcome the consequences for those who have experienced justice system involvement, it could potentially confound the results regarding TRDM's potential to overcome the risk of peer deviance.

Contrary to common depictions of youth crime as an urban problem, arrest can be a somewhat prevalent and salient experience in the lives of non-urban adolescents. Researchers have found urban youth are more likely to be given a formal label (Matsueda et al., 1992). Yet, incarceration in rural areas has increased, even as it subsides in other areas (Kang-Brown & Subramanian, 2017). While some of the incarcerated population comes from outside of the rural areas, it still may be true that

arrest and other domains of justice system involvement are growing more prevalent. There is some evidence that punitive attitudes and practices are increasing in rural areas. In fact, many rural communities see themselves as "moral communities" under threat, and are thus particularly unwelcoming to deviations from their way of life (Wuthnow, 2019). Rural areas tend to be less tolerant of deviation from their norms, and may deal more harshly with juveniles in particular, whose misbehavior is often seen as a serious problem (Weisheit et al., 2006). The proportion of rural schools with embedded law enforcement officers has also increased, which naturally brings with it increased surveillance and increased likelihood of adolescent delinquency being dealt with in a formal manner (Musu-Gillette et al., 2017; Na & Gottfredson, 2013).

Arrest may not only be especially prevalent, but also especially stigmatizing for youth in rural communities. The close-knit ties and strong social norms typical in rural communities can lead to experiencing greater social consequences after justice system involvement. Anonymity is not especially likely; in less populated areas with close ties, news of justice system contact can spread between peers and their parents. Even those working for the justice system may know the youth or his or her family. This can lead to exclusion from conventional opportunities, including conventional peers. Jacobsen and colleagues (2018), using the PROSPER Peers data, indeed find that arrested adolescents have less prosocial friends due to both them pulling away from conventional friendships and conventional peers pulling away from them. Arrest is associated with less of a reduction in friendship nominations in larger networks (Jacobsen et al., 2018), supporting the idea that adolescents residing in smaller, more dense networks – common in rural communities – may experience a higher degree of

stigma after arrest. Moreover, this stigma would impact the ability of students to "opt in" to more prosocial friendships. Adolescents who have been arrested may be less likely to experience the benefits of social capital in rural areas that are typically characterized by cultural homogeneity (Sherman, 2006).

As such, I conduct sensitivity analyses controlling for prior arrest. Arrest here is measured as the being picked up by the police for misbehavior – whether or not that formally constitutes an arrest in that specific police department. This measure, while not representing a severe degree of justice system contact, is appropriate because a substantial enough proportion of juveniles experience arrest (Brame et al., 2012, 2014), though they are not especially likely to experience confinement thereafter. Specifically, I include a dichotomous variable measuring whether the adolescent had ever been arrested at any prior wave. In Jacobsen and colleague's (2018) analysis of PROSPER Peers youth, about 22% of students had experienced at least one arrest by the spring of their junior year. Similarly, my results show that 21.13% of my sample had experienced at least one arrest by the spring of their junior year (see Table 16).

Table 16. Percent of Sample that Reported an Arrest at Current Wave or any Wave Prior*

	6th grade	*7th grade*	*8th grade*	*9th grade*	*10th grade*	*11th grade*
% Arrested	5.5%	8.51%	11.87%	15.38%	18.06%	21.13%

***** These estimates are based on student reports of arrests in the past 12 months at this wave and any wave prior. The survey in the fall of 6th grade, which is not otherwise included in the analysis, is included in the construction of this measure.

Though arrest does significantly decrease the likelihood of resilience, TRDM and deviant peer influence continue to act in the predicted directions in the direct interaction models (Table 17). There is still no evidence of a significant linear

interaction. The direct multigroup models also demonstrate similar results, despite arrest acting as a significant predictor (Table 18). The results of the indirect models (Tables 19 and 20) remain substantively identical to the main models. In the indirect interaction models, arrest does exert a direct impact on resilience in all waves and an indirect impact on resilience, through prompting a change to the deviance of one's networks, in all waves except the last (Table 19). This provides some support for the tenets of labeling theory that state formal criminal justice system involvement, even a relatively minor experience, can increase delinquency, at least in part due to cutting individuals off from conventional others (Becker, 1963). The results in the multigroup indirect models are less clear-cut, as coefficients and significance levels vary by wave and level of deviant peer exposure, but still show evidence of a direct and/or indirect effect of arrest on resilience at each wave (Table 20).

Table 17. Direct Effect of TRDM on Resilience in Interaction Models Including Arrest

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DP Prop	-.28**	.11	-.30***	.09	-.31**	.10	-.22**	.08
TRDM	.11**	.03	.09**	.03	.12***	.02	.05*	.02
TRDM * DP	.06	.09	-.06	.07	-.01	.09	-.09	.09
Arrest	-.34**	.12	-.28***	.07	-.15*	.07	-.18*	.07
N	5,248		6,360		6,625		6,164	
χ^2	42.18***		11.68***		15.41***		24.51***	
RMSEA	.09		.04		.05		.06	
CFI	.97		.99		.99		.98	

SRMR	.01	.01	.01	.01

DP refers to Deviant Peers. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 18. Direct Effect of TRDM on Resilience in Multigroup Models Including Arrest

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
TRDM	.12*	.11†	.25***	.04	CFI = .97;
	(.05)	(.06)	(.06)	(.09)	RMSEA = .03;
Arrest	-.02	-.86***	-.04	-.56*	SRMR = .06;
	(.23)	(.24)	(.20)	(.26)	$\chi^2 = 441.63$***
N	*2,277*	*1,794*	*828*	*559*	
$7^{th} – 9^{th}$					
TRDM	.03	.12**	.23***	.01	CFI = .97
	(.04)	(.04)	(.06)	(.07)	RMSEA = .02
Arrest	-.64**	-.05	-.20	-.56*	SRMR = .06
	(.20)	(.10)	(.15)	(.22)	$\chi^2 = 448.24$***
N	*2,364*	*2,199*	*1,259*	*734*	
$8^{th} – 10^{th}$					
TRDM	.14**	.12*	.15*	.22**	CFI = .97
	(.05)	(.05)	(.06)	(.07)	RMSEA = .03
Arrest	-.32†	-.07	-.21	-.25†	SRMR = .07
	(.18)	(.12)	(.15)	(.15)	$\chi^2 = 491.68$***
N	*2,122*	*2,247*	*1,512*	*1,004*	
$9^{th} – 11^{th}$					
TRDM	.18	.02	.09	.01	CFI = .97
	(.05)	(.05)	(.06)	(.07)	RMSEA = .03
Arrest	-.07	-.33**	-.16	-.15	SRMR = .06
	(.13)	(.12)	(.16)	(.17)	$\chi^2 = 478.61$***
N	*1,895*	*2,005*	*1,416*	*1,103*	

DP refers to Deviant Peers. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 19. Indirect Effect of TRDM on Resilience in Interaction Models Including Arrest

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DV: Δ DP Prop								
TRDM	.00	.01	-.02**	.01	-.00	.01	-.01	.01
TRDM*DP	.06***	.02	.05**	.02	.02	.02	-.01	.02
Arrest	.05†	.02	.02	.02	.03*	.01	-.01	.01
DV: Resilience								
Δ DP Prop	-.38***	.08	-.36***	.08	-.46***	.08	-.25**	.08
DP Prop	-.57***	.13	-.56***	.10	-.61***	.10	-.38***	.09
TRDM	.12**	.03	.09**	.03	.12***	.02	.04*	.02
Indirect Effect	-.00	.00	.01*	.00	.00	.00	.00	.00
Total Effect	.11**	.03	.09**	.03	.12***	.02	.05*	.02
TRDM*DP	-.04	.09	-.04	.07	.00	.09	-.09	.09
Indirect Effect	-.02**	.01	-.02*	.01	-.01	.01	.00	.00
Total Effect	-.06	.09	-.06	.07	-.01	.09	-.09	.09
Arrest	-.32**	.12	-.27***	.07	-.14*	.07	-.18*	.07
Indirect Effect	-.04**	.01	-.02***	.01	-.18**	.07	-.01	.01
Total Effect	-.36**	.11	-.29***	.07	-.04***	.01	-.19*	.07
N	5,248		6,360		6,625		6,164	
χ^2	42.18***		11.68*		15.41***		24.51***	
RMSEA	.09		.04		.05		.06	
CFI	.98		.99		.99		.99	
SRMR	.01		.01		.01		.01	

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 20. Indirect Effect of TRDM on Resilience in Multigroup Models Including Arrest

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
	On Δ DP Prop				
TRDM	.01	.03*	.01	.03	
	(.01)	(.01)	(.02)	(.02)	
Arrest	.08*	.02	-.00	.10†	
	(.04)	(.04)	(.04)	(.06)	
	On Resilience				
Δ DP Prop	-.46**	-.25*	-.39*	-.19	
	(.13)	(.13)	(.18)	(.17)	
TRDM	.12*	.12†	.25***	.05	CFI = .97
	(.05)	(.06)	(.06)	(.09)	RMSEA = .03
Indirect Effect	.01	-.01	.00	-.01	SRMR = .05
	(.01)	(.00)	(.01)	(.01)	χ^2 =
Total Effect	.12**	.11†	.25***	.04	460.17***
	(.05)	(.06)	(.06)	(.01)	
Arrest	.01	-.86***	-.04	-.54*	
	(.23)	(.24)	(.20)	(.26)	
Indirect	-.06†	-.03	-.09*	-.03	
	(.03)	(.02)	(.04)	(.03)	
Total	-.04	-.88***	-.13	-.57*	
	(.22)	(.25)	(.21)	(.25)	
N	*2,277*	*1,794*	*828*	*559*	
$7^{th} – 9^{th}$					CFI = .97
	On Δ DP Prop				RMSEA = .02
TRDM	-.04***	-.02	-.01	.02	SRMR = .05
	(.01)	(.01)	(.01)	(.02)	χ^2 =
Arrest	.01	.04	-.01	.02	466.16***
	(.03)	(.03)	(.04)	(.05)	

	On Resilience				
Δ DP Prop	-.38**	-.30*	-.55**	-.00	
	(.12)	(.13)	(.17)	(.19)	
TRDM	.02	.11*	.22**	.01	
	(.05)	(.05)	(.06)	(.07)	
Indirect Effect	.01*	.01	.01	-.00	
	(.01)	(.01)	(.01)	(.00)	
Total Effect	.03	.12**	.23***	.01	
	(.04)	(.04)	(.06)	(.07)	
Arrest	-.64**	-.04	-.21	-.55*	
	(.20)	(.10)	(.16)	(.22)	
Indirect Effect	-.01	-.03*	-.03	-.00	
	(.20)	(.02)	(.03)	(.02)	
Total Effect	-.65**	-.07	-.23	-.56*	
	(.01)	(.10)	(.15)	(.22)	
N	*2,364*	*2,199*	*1,259*	*734*	
$8^{th} – 10^{th}$					
	On Δ DP Prop				
TRDM	-.00	-.02†	.04*	-.03	
	(.01)	(.01)	(.01)	(.02)	
Arrest	.08**	.02	.01	.06	
	(.03)	(.03)	(.03)	(.04)	
	On Resilience				
Δ DP Prop	-.57***	-.31*	-.46***	-.47**	
	(.12)	(.14)	(.12)	(.14)	
TRDM	.13*	.12*	.16**	.20**	CFI = .97
	(.05)	(.05)	(.06)	(.06)	RMSEA =
Indirect Effect	.00	.01	-.02*	.01	.02
	(.01)	(.00)	(.01)	(.01)	SRMR = .06
Total Effect	.14**	.12*	.15*	.21**	χ^2 =
	(.05)	(.05)	(.06)	(.07)	509.87***
Arrest	-.27	-.06	-.21	-.22	
	(.17)	(.11)	(.15)	(.14)	
Indirect Effect	-.07**	-.03*	-.03†	-.05†	
	(.02)	(.02)	(.02)	(.03)	
Total Effect	-.33†	-.10	-.24†	-.27†	
	(.18)	(.12)	(.15)	(.15)	
N	*2,123*	*2,248*	*1,514*	*1,006*	
$9^{th} – 11^{th}$					CFI = .96

	On Δ DP Prop				RMSEA = .02
TRDM	-.00	.00	.00	-.04*	SRMR = .06
	(.01)	(.01)	(.02)	(.02)	χ^2 =
Arrest	-.04	-.00	.02	-.01	494.47***
	(.03)	(.02)	(.04)	(.04)	
	On Resilience				
Δ DP Prop	-.26†	-.13	-.31*	-.27	
	(.14)	(.12)	(.15)	(.22)	
TRDM	.08	.03	.09	.00	
	(.05)	(.05)	(.06)	(.07)	
Indirect Effect	.00	-.00	-.00	.01	
	(.00)	(.00)	(.01)	(.01)	
Total Effect	.08	.03	.09	.01	
	(.05)	(.05)	(.06)	(.07)	
Arrest	-.08	-.33**	-.15	-.16	
	(.13)	(.12)	(.13)	(.16)	
Indirect Effect	-.00	-.01	-.01	.00	
	(.01)	(.01)	(.01)	(.02)	
Total Effect	-.08	-.34**	-.17	-.15	
	(.13)	(.12)	(.13)	(.16)	
N	*1,895*	*2,005*	*1,416*	*1,103*	

DP refers to Deviant Peers. Δ signifies change. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Serious Forms of Delinquency

To acknowledge that some delinquency in adolescence is normal, and to examine how results differ when narrowing in on more serious forms of adolescent delinquency, I conduct sensitivity analyses with only the most serious and rare delinquency items as part of the dichotomous outcome measure. The dependent variable for these analyses was a dichotomous variable (1 = no delinquency and 0 = any delinquency) measuring whether adolescents had, in the last 12 months, reported engaging in any of these behaviors: 1) taken something worth $25 or more that didn't belong to them, 2) broken into or tried to break into a building just for fun or to look

around, 3) beat up someone or physically fought with someone because they made you angry (other than just playing around), and 4) carried a hidden weapon. These items were specifically chosen because these acts were less common than many other delinquency items among the adolescents and were serious enough to potentially lead to felony charges, which could "ensnare" adolescents in the negative fallout of involvement in the criminal justice system (see Moffit, 1993). Averaging across the waves, about 30% of the sample had engaged in one of these acts in the past 12 months.

The direct interaction model supports similar conclusions to the main models, where a higher proportion of deviant peers is associated with a lower probability of resilience, higher TRDM is associated with an increased probability of resilience, and there is no evidence of a linear interaction between the two (Table 21). There is a notable increase in the magnitude of the effect of the proportion of deviant peers on the likelihood of resilience amongst the adolescents from 8^{th} – 10^{th} grade. The multigroup model (Table 22) does show some differences. From 6^{th}-8^{th} grade, the effect of TRDM on resilience to deviant peer influence is no longer significant. In some other instances, the estimates of TRDM's impact grow larger (for example, many of the effect sizes from the 8^{th}-10^{th} grade). TRDM is now significantly associated with an increase in resilience for those with a mid-level of deviant peers, rather than a high level of deviant peers, from 9^{th} – 11^{th} grade. In tests for equality of TRDM's coefficients across level of deviant peer exposure, I find significant differences in those with medium exposure from 7^{th} – 9^{th} grade and for those with all deviant peers from 8^{th} – 10^{th} grade, unlike the results of the tests for the main models.

Overall, there is still support for the effectiveness of TRDM in bolstering resilience for those who are exposed to a mid-to-high proportion of deviant peers across waves.

Table 21. Direct Effect of TRDM on Resilience to Serious Delinquency in Interaction Models

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß	SE	ß	SE	ß	SE	ß	SE
DP Prop	-.25*	.11	-.39***	.11	-.52***	.11	-.23†	.08
TRDM	.10*	.04	.14***	.03	.17***	.03	.09*	.04
TRDM * DP	.02	.12	-.04	.10	.07	.10	-.10	.12
N	5,249		6,365		6,625		6,165	
χ^2	42.68***		12.74***		15.50***		25.85***	
RMSEA	.09		.04		.05		.06	
CFI	.97		.99		.99		.97	
SRMR	.02		.01		.01		.01	

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 22. Direct Effect of TRDM on Absence of Serious Delinquency in Multigroup Models

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
TRDM	.09 (.06)	.11 (.07)	.07 (.10)	.19 (.13)	CFI = .97; RMSEA = .03; SRMR = .07;
N	*2,276*	*1,792*	*692*	*559*	χ^2 = 428.84***
$7^{th} – 9^{th}$					
TRDM	.05 (.07)	.26*** (.06)	.20* (.10)	.05 (.09)	CFI = .97 RMSEA = .03 SRMR = .06

N	*2,364*	*2,198*	*1,131*	*736*	$\chi^2 = 439.98$***
$8^{th} - 10^{th}$					
					CFI = .97
TRDM	.21**	.13**	.19*	.45***	RMSEA = .03
	(.07)	(.07)	(.07)	(.09)	SRMR = .06
N	*2,121*	*2,245*	*1,414*	*1,004*	$\chi^2 = 460.06$***
$9^{th} - 11^{th}$					
					CFI = .96
TRDM	.04	.18*	.08	.11	RMSEA = .03
	(.08)	(.08)	(.10)	(.08)	SRMR = .07
N	*1,895*	*2,005*	*1,237*	*1,102*	$\chi^2 = 459.42$***

DP refers to Deviant Peers. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

The indirect interaction models predicting absence of serious delinquency (Table 23) lead to very similar conclusions as the main models; there is little evidence of an indirect effect of TRDM on resilience besides a small indirect effect for the 7^{th} – 9^{th} grade model. There is an increase in the magnitude of the coefficients for deviant peer proportion and the change in deviant peer proportion during the last two waves (8^{th} – 11^{th} grade). The negative impact of deviant peers on resilience appears to be more pronounced when examining only serious delinquency, and TRDM estimates maintain their direction and significance. The multigroup indirect models (Table 24) sees similarly reduced significance of TRDM in the model from 6^{th} – 8^{th} grade, with no clear support for an indirect effect of TRDM. Overall, models defining resilience as lack of serious delinquency lead to similar conclusions, with slightly larger estimates of the influence of deviant peer exposure in some models.

Table 23. Indirect Effect of TRDM on Absence of Serious Delinquency in Interaction Models

	6^{th}-8^{th}		7^{th}-9^{th}		8^{th} – 10^{th}		9^{th}- 11^{th}	
	ß	SE	ß	SE	ß	SE	ß	SE
DV: Δ DP Prop								
TRDM	.00	.01	-.02**	.01	-.00	.01	-.01	.01
TRDM*DP	.06***	.02	.05**	.02	.02	.02	-.01	.02
DV: Resilience								
Δ DP Prop	-.43***	.09	-.33**	.11	-.60***	.11	-.40**	.12
DP Prop	-.58***	.14	-.63***	.14	-.90***	.14	-.49**	.15
TRDM	.10*	.04	.13***	.03	.17***	.03	.09*	.04
Indirect Effect	-.00	.00	.01*	.00	.00	.00	.00	.00
Total Effect	.10*	.04	.14***	.03	.17***	.04	.09*	.04
TRDM*DP	.04	.12	-.07	.10	.10	.10	-.07	.12
Indirect Effect	-.02**	.01	-.02*	.01	-.01	.01	.00	.01
Total Effect	.02	.12	-.06	.06	.09	.10	-.07	.12
N	5,249		6,365		6,626		6,165	
χ^2	42.68***		5.50*		39.52***		92.55***	
RMSEA	.09		.03		.08		.12	
CFI	.98		.99		.98		.95	
SRMR	.01		.00		.01		.02	

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 24. Indirect Effect of TRDM on Resilience to Serious Delinquency in Multigroup Models

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
$6^{th} – 8^{th}$					
	On Δ DP Prop				
TRDM	-.01	.02*	.00	.03	
	(.01)	(.01)	(.02)	(.02)	
	On Resilience				
Δ DP Prop	-.28†	-.52**	-.68**	-.37	CFI = .97
	(.15)	(.18)	(.25)	(.26)	RMSEA = .03
TRDM	.08	.12†	.08	.20	SRMR = .06
	(.06)	(.07)	(.10)	(.13)	χ^2 = 433.85***
Indirect Effect	.00	-.01*	-.00	-.01	
	(.00)	(.01)	(.01)	(.01)	
Total Effect	.09	.10	.08	.19	
	(.06)	(.07)	(.10)	(.13)	
N	*2,278*	*1,793*	*692*	*559*	
$7^{th} – 9^{th}$					
	On Δ DP Prop				
TRDM	-.04***	-.02	-.02	.01	
	(.01)	(.01)	(.01)	(.02)	
	On Resilience				CFI = .97
Δ DP Prop	-.29	-.35*	-.50**	.23	RMSEA = .02
	(.21)	(.16)	(.18)	(.24)	SRMR = .05
TRDM	.04	.25***	.19†	.05	χ^2 = 460.32***
	(.07)	(.06)	(.10)	(.09)	
Indirect Effect	.01	.01	.01	.00	
	(.01)	(.00)	(.01)	(.01)	
Total Effect	.05	.26***	.20*	.05	
	(.07)	(.06)	(.10)	(.09)	
N	*2,366*	*2,199*	*1,131*	*736*	
$8^{th} – 10^{th}$					
	On Δ DP Prop				
TRDM	-.01	-.02†	.03*	-.03	CFI = .97
	(.01)	(.01)	(.01)	(.02)	

	On Resilience				RMSEA = .03
Δ DP Prop	-.56**	-.74***	-.53*	-.06	SRMR = .06
	(.19)	(.17)	(.22)	(.19)	χ^2 =
TRDM	.21**	.12†	.20**	.44***	479.53***
	(.07)	(.06)	(.07)	(.09)	
Indirect Effect	.00	.01†	-.02†	.00	
	(.01)	(.01)	(.01)	(.01)	
Total Effect	.21**	.13*	.19*	.44***	
	(.07)	(.07)	(.07)	(.09)	
N	*2,123*	*2,247*	*1,417*	*1,006*	
$9^{th} - 11^{th}$					
	On Δ DP Prop				
TRDM	.00	.00	-.00	-.04*	
	(.01)	(.01)	(.02)	(.02)	CFI = .96
	On Resilience				RMSEA = .03
Δ DP Prop	-.35	-.26†	-.27	-.90**	SRMR = .06
	(.22)	(.16)	(.21)	(.28)	χ^2 =
TRDM	.04	.19*	.08	.07	477.36***
	(.08)	(.08)	(.10)	(.11)	
Indirect Effect	-.00	-.00	.00	-.04†	
	(.00)	(.00)	(.00)	(.02)	
Total Effect	.05	.19*	.08	.11	
	(.08)	(.08)	(.10)	(.12)	
N	*1,895*	*2,005*	*1,237*	*1,102*	

DP refers to Deviant Peers. Δ signifies change. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Using Maximum Likelihood Estimator

SEM has many different possible estimation techniques for the equations; in the main models presented here, I use a robust weighted least square estimator (WSLMV), which is recommended in the case of a dichotomous dependent variable (Suh, 2015). However, some suggest that robust maximum likelihood estimators (MLR) are also effective to use with a dichotomous dependent variable. Though these

estimates have less power, they better control Type 1 error (Bandalos, 2014; Suh, 2015). I estimate the indirect and direct interaction models with MLR methods in sensitivity analyses to investigate whether using robust maximum likelihood estimation procedures leads to any changes in results. I was unable to run the multigroup models using a maximum likelihood estimator, as that is not accommodated for dichotomous dependent variables using Mplus (Muthén & Muthén, 1998-2010).

Though the magnitude of the estimates cannot be directly compared to the models estimated using WSLMV (due to different interpretations of the coefficients, as WSLMV uses probit regression and MLR uses logistic regression), the statistically significant estimates in both the direct interaction model (Table 25) and the indirect interaction model (Table 26) are the same as those in the main models. The coefficients in the MLR models are the same direction and relative magnitude of the coefficients in the WSLMV models (i.e., TRDM has the largest estimated positive impact on resilience on from 8^{th} – 10^{th} grade using both estimators), providing evidence of robustness of the WSLMV findings.

Table 25. Direct Effect of TRDM on Resilience in Interaction Models using Robust Maximum Likelihood Estimator

	6^{th}-8^{th}		*7^{th}-9^{th}*		*8^{th} – 10^{th}*		*9^{th}- 11^{th}*	
	ß (OR)	SE	ß (OR)	SE	ß (OR)	SE	ß (OR)	SE
DP Prop	-.48** (.62)	.18	-.54*** (.59)	.14	-.55** (.58)	.16	-.40** (.67)	.13
TRDM	.19** (1.21)	.06	.16*** (1.17)	.04	.21*** (1.23)	.04	.08* (1.09)	.04
TRDM * DP	-.08 (.92)	.15	-.05 (.96)	.11	.02 (1.02)	.15	-.14 (.87)	.15
N	5,249		6,367		6,626		6,165	

DP refers to Deviant Peers. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000.

Table 26. Indirect Impact of TRDM on Resilience in Interaction Models using Robust Maximum Likelihood Estimator

	6th-8th		*7th-9th*		*8th – 10th*		*9th- 11th*	
	ß (OR)	SE	ß (OR)	SE	ß (OR)	SE	ß (OR)	SE
DV: Δ DP Prop								
TRDM	.00 (1.00)	.01	-.02** (.98)	.01	-.00 (1.00)	.01	-.01 (.99)	.01
TRDM*DP	.06** (1.06)	.02	.05** (1.05)	.02	.02 (1.02)	.02	-.00 (1.00)	.02
DV: Resilience								
Δ DP Prop	-.64*** (.53)	.14	-.59*** (.55)	.12	-.78*** (.46)	.13	-.40** (.67)	.14
DP Prop	-.97*** (.38)	.21	-.97*** (.38)	.17	-1.05*** (.35)	.10	-.66*** (.51)	.16
TRDM	.20** (1.22)	.06	.15** (1.16)	.04	.21*** (1.24)	.04	.09* (1.09)	.04
Indirect Effect	-.00 (1.00)	.00	.01* (1.01)	.00	.00 (1.00)	.02	.00 (1.00)	.00
Total Effect	.19** (1.21)	.06	.16*** (1.17)	.04	.22*** (1.24)	.04	.09* (1.09)	.04
TRDM*DP	-.05 (.95)	.16	-.02 (.98)	.11	.03 (1.03)	.15	-.15 (.86)	.16
Indirect Effect	-.04* (.97)	.02	-.03* (.97)	.01	-.02 (.98)	.02	.00 (1.00)	.01
Total Effect	-.08 (.92)	.16	-.05 (.95)	.11	.01 (1.01)	.15	-.15 (.87)	.16
N	5,249		6,367		6,626		6,165	

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000.

Examining Attrition

There was some attrition over the course of the six waves. This attrition was driven primarily by people moving out of the school districts, with students participating for an average of 4 waves. There was, however, statistically significant

differences between the adolescents who were found in all waves compared to those who were not (see Table 27). Adolescents with no attrition were more likely to avoid delinquency, had a lower proportion of deviant friends, had higher TRDM, and engaged in less prior deviance. They were also more likely to be white, were of a higher socioeconomic status, had more parental monitoring and better parental relations, were less impulsive, spent less time UUS, and had more friend nominations. In order to examine if these differences biased the results, I compare the model results for only the 6th grade adolescents who do not have any attrition (participated in all waves) in order to see if the results for this sample differs from the main models.

Table 27. Descriptive Statistics for 6th Grade Students with or without Attrition

	No Attrition		*Attrition*	
	Mean or %	SD	Mean or %	SD
No Delinquency[a] ***	58%	--	41.70%	--
Δ DP Proportion[b]	-.03	.32	-.02	.36
DP Proportion***	.45	.24	.53	.27
TRDM***	.17	.92	-.08	1.02
Prior deviance***	33.02%	--	46.63%	--
Male	52.54%	--	51.89%	--
White***	88.73%	--	81.78%	--
Free Lunch***	-.49	1.58	.51	1.58
Parental Monitoring***	4.49	.62	4.31	.76
Parent Relations***	.11	.37	.02	.43
Impulsivity***	2.51	1.33	2.65	1.40
UUS***	7.05	3.19	7.48	3.28
# of Nominations***	5.50	1.68	4.99	1.88
Tx Condition	45.4%	--	44.12%	--
N (%)	3,993 (69.83%)		1,725 (30.17%)	

DP refers to Deviant Peers. Δ signifies change. UUS refers to unsupervised, unstructured socializing.
[a] Measured at Time 3. [b] Measured at Time 2. † p < .10 * p < .05 ** p < .01 *** = p < .000 in a t-test or Chi-square test between 6th grade students who eventually leave the sample and those who do not.

The interaction models, both direct and indirect, show no meaningful differences (see Tables 28 and 30). The multigroup models show a few small

differences for students with no attrition (see Tables 29 and 31). For students with a high proportion of deviant peers, TRDM had a more sizable association with resilience. For those with a low proportion of deviant peers, TRDM was less likely to have a significant impact. For those with a mid-proportion of deviant peers, the impact of a change in deviant peer proportion was reduced to insignificance. Overall, however, the estimates for students with no attrition were in the same direction and of a similar magnitude, and some estimates losing statistical significance in the multigroup models may be linked to the loss of power due to reduced sample sizes.

Table 28. Direct Effect of TRDM on Resilience in Interaction Model for 6th Grade Students with No Attrition

	Full Sample		*No Attrition*	
	ß	SE	ß	SE
DP Prop	-.29**	.11	-.23*	.11
TRDM	.12**	.03	.11**	.03
TRDM * DP	-.05	.09	.01	.11
N	5,249		3,682	
χ^2	46.07***		43.62***	
RMSEA	.09		.11	
CFI	.97		.96	
SRMR	.02		.01	

DP refers to Deviant Peers. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 29. Direct Effect of TRDM on Resilience in Multigroup Models for 6th Grade Students with No Attrition

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
Full Sample					
TRDM	0.13*	.11†	.28***	.04	CFI = .97; RMSEA = .03; SRMR = .07;
	(.06)	(.06)	(.07)	(.10)	
N	*2,278*	*1,794*	*692*	*559*	χ^2 = 414.37***
No Attrition					
TRDM	.10†	.12†	.36***	.09	CFI = .97 RMSEA = .03 SRMR = .07
	(.06)	(.07)	(.08)	(.12)	
N	*1,726*	*1,265*	*437*	*304*	χ^2 = 367.57***

DP refers to Deviant Peers. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 30. Indirect Effect of TRDM on Resilience in Interaction Models for 6th Grade Students with no Attrition

	Full Sample		*No Attrition*	
	ß	SE	ß	SE
DV: Δ DP Prop				
TRDM	.00	.01	.01	.01
TRDM*DP	.06***	.02	.07**	.02
DV: Resilience				
Δ DP Prop	-.39***	.08	-.34***	.09
DP Prop	-.58***	.13	-.49***	.13
TRDM	.12***	.03	.11**	.03
Indirect Effect	-.00	.00	-.00	.00
Total Effect	.12**	.03	.11**	.03
TRDM*DP	-.03	.09	.03	.11
Indirect Effect	-.02**	.01	-.02*	.01

Total Effect	-.05	.09	.01	.11
N	5,249		3,682	
χ^2	46.07***		43.62***	
RMSEA	.09		.11	
CFI	.98		.97	
SRMR	.01		.01	

DP refers to Deviant Peers. Δ signifies change. TRDM * DP refers to the interaction term between TRDM and the deviant peer proportion. † p < .10 * p < .05 ** p < .01 *** = p < .000. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Table 31. Indirect Effect of TRDM on Resilience in Multigroup Models for 6th Grade Students with No Attrition

	Low DP ß (SE)	Mid DP ß (SE)	High DP ß (SE)	All DP ß (SE)	Model Fit
Full Sample					
	On Δ DP Prop				
TRDM	-.01 (.01)	.03* (.01)	.01 (.02)	.03 (.02)	
	On Resilience				
Δ DP Prop	-.47** (.14)	-.26* (.12)	-.40* (.18)	-.22 (.17)	CFI = .97 RMSEA = .03 SRMR = .06 χ^2 = 432.68***
TRDM	.12* (.05)	.12† (.06)	.28*** (.07)	.05 (.10)	
Indirect Effect	.01 (.01)	-.01 (.00)	-.00 (.01)	-.01 (.01)	
Total Effect	.13* (.06)	.11† (.06)	.28*** (.07)	.04 (.01)	
N	2,278	1,794	692	559	
No Attrition					
	On Δ DP Prop				CFI = .97 RMSEA = .03 SRMR = .06 χ^2 = 386.85***
TRDM	-.01 (.01)	.03** (.01)	.02 (.02)	.04 (.03)	
	On Resilience				

Δ DP Prop	-.37*	-.21	-.35**	-.33
	(.14)	(.15)	(.24)	(.25)
TRDM	.09	.13*	.37***	.10
	(.06)	(.06)	(.08)	(.12)
Indirect Effect	.01	-.01	-.01	-.01
	(.01)	(.01)	(.01)	(.01)
Total Effect	.10†	.12†	.36***	.09
	(.06)	(.07)	(.08)	(.12)
N	1,726	1,265	437	304

DP refers to Deviant Peers. Δ signifies change. † $p < .10$ * $p < .05$ ** $p < .01$ *** = $p < .000$. CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Squared Residual.

Examining Change in Friendship Groups

In my sample, only 3,099 student/year observations (11.83%) exhibited no change in the deviant proportion of their friend group at Time 2. That implies quite a bit of change; yet, it is uncertain whether this change lies in the adolescents' friends changing their behavior or the adolescents changing their friends. If the deviance of one's friend group is changing because adolescents' friends are committing more or less crime, and not because adolescents are changing their friends to be more in line with their preferences, this is inconsistent with my hypothesis of agentic peer selection. As such, I investigated whether changes in peer group deviance reflect a change in the youths' friendships.

A descriptive analysis of the data reveals a great deal of change to the adolescents' friend groups in my sample. Only about 3% of the student/year observations had the same exact set of friends at the following wave, while about 28% terminated friendships but did not make new friends. The remaining 71% of the student/year observations had at least one new friend in the following year. This signifies that most of these adolescents' social networks were in flux.

An equal proportion of the adolescents' new friends and friends who stayed the same were deviant – about 45% of both groups. Yet, there is evidence that some of the positive change in the peer group was linked to new friendships. Those whose proportion of deviant peers went up in the following wave had an average of 1.41 new friends and 1.07 same friend nominations.[24] Those whose proportion of deviant peers went down in the following wave had an average of 2.53 new friends and 1.81 same friend nominations. Thus, for adolescents who had a change to the deviance of their friend groups, over half of their network was comprised of new friends. The importance of new friendships is more pronounced for those who had a decrease in their deviant peer proportion; about 11% of those whose friend group became less deviant had only the same friends. Comparatively, 47% of those whose friend group became more deviant had only the same friends. This demonstrates that those who reduced the delinquency of their friend group were especially likely to have new friends.

Selecting more prosocial friends was also associated with resilience in the next wave. Adolescents who displayed resilience versus delinquency did not differ much on the number of new friends (2.18 for the "resilient" adolescents versus 2.11 for those who engaged in delinquency) or the number of friends they kept in the next wave (1.74 versus 1.50, respectively). But for those who displayed resilience, the new friends that they selected were less likely to be deviant; about 39% of the new friends were deviant versus 50% amongst the same friends.

[24] For the calculations that require information about the friends' deviance, I count only the friend nominations that can be linked to information about their level of deviance.

The multivariate models find a reduction in the proportion of deviant friends to be linked to an increased probability of resilience, and these descriptive analyses suggest that this change is likely to be linked to new friendships. Additionally, I ran models that decomposed delinquent peer exposure in the next wave into four different categories: a change in the behavior of friends that stayed the same, the proportion of new friends that were deviant, the proportion of deviant ties from the last wave that were severed, and the proportion of non-deviant ties from the last wave that were severed. These results demonstrated that, of the four measures, a lower proportion of deviance amongst new friends was accompanied by the most consistent and largest increase in resilience (or, conversely, higher deviance amongst new friends was most consistently associated with decreased resilience).[25]

This supports an argument presented in the literature review: adolescents can change their level of prosocial capital by selecting new, less deviant friends, which will increase the likelihood of resilience at later waves. Selection of non-deviant friends at later waves appears particularly important for prompting resilience. However, I cannot rule out the possibility that severed ties and new friendships could be initiated by the friend, and not the subject of these analyses (though many of the adolescent's friends would also be a subject of these analyses themselves). As such, I cannot say for certain whether these tie changes represent the adolescents acting with agency and selecting into more prosocial friend groups. Additionally, across waves and levels of peer exposure, higher TRDM is not consistently linked to a positive

[25] Keeping non-deviant ties was also associated with an increased likelihood of resilience, though less consistently and smaller in magnitude. Keeping deviant ties and change in the behavior of same friends were not consistently related to resilience.

change in the delinquency of adolescents' friend groups.[26] According to Paternoster and Pogarsky (2009), TRDM represents an operationalization of agency, so this reduces support for the argument that the adolescents are acting with agency in the selection of prosocial peer groups.

Summary of Results

Tables 32 and 33 give an overall summary of results for the interaction and multigroup models, respectively, allowing for more examination of the evidence for each of my hypotheses. Table 33 also reports the results of the sensitivity analyses that removed the lagged dependent variable, focused only on more serious delinquency, and used maximum likelihood estimation, since these analyses did show some departures from the results of the main model.

- *Hypothesis 1: TRDM will be positively associated with resilience.*

Both the interaction and multigroup models provide support that TRDM is positively associated with resilience, in accordance with Hypothesis 1. Higher TRDM is never negatively associated with the likelihood of resilience for any of the waves or across any levels of deviant peer exposure (though it sometimes has no statistically significant effect, most notably in multigroup models from 9^{th} – 11^{th} grade and multigroup models of serious delinquency only from 6^{th}-8^{th} grade).

[26] The analyses that decompose deviant peer exposure at the next wave do show some evidence that higher TRDM may lead to less deviance amongst new friends and keeping more non-deviant ties. However, they also provide some evidence that higher TRDM is associated with keeping more deviant ties, as well, and that those with both high TRDM and a high level of deviant peer exposure may select and keep more deviant friends. Overall, the evidence for an indirect effect of TRDM on resilience through prompting positive change to friendship groups is still not compelling.

- *Hypothesis 2: TRDM will be especially protective at high levels of deviant peer exposure.*
    - *Hypothesis 2a: The interaction between deviant peer exposure and TRDM will have a positive association with resilience.*
    - *Hypothesis 2b: The positive association of TRDM with resilience will be larger in magnitude for adolescents with a higher level of deviant peer exposure in the multigroup models.*

The results regarding Hypothesis 2, though mixed, do provide some support. There is no evidence of a *linear* interaction, where TRDM becomes more protective the higher an adolescent's level of exposure to deviant peers (no evidence for Hypothesis 2a). The multigroup models, however, provide evidence of a *non-linear* interaction whereby TRDM has the greatest impact for adolescents with a high degree of deviant peers – but not *all* deviant peers – for most waves (supporting Hypothesis 2b). The estimate of TRDM is the largest in magnitude for those in the high deviant peer group for the waves beginning in 6th and 7th grades in most models; one exception is the analyses estimating only serious delinquency, where TRDM had the largest estimate amongst the mid DP group in 7th grade and was only significant for the mid DP group in 9th grade. The results for 8th grade do differ, with the largest positive impact of TRDM amongst those with an entirely deviant peer group, though this difference is only statistically significant in the analyses estimating serious delinquency. Across all waves and all analyses, this does provide support for the hypothesis that TRDM is especially protective for those at the higher levels of deviant peer exposure – estimates of the effect of TRDM on resilience are consistently lowest

in magnitude for those with the lowest level of deviant peer exposure, and estimates for those with a high degree of deviant peers are most likely to significantly exceed those of other groups.

- *Hypothesis 3: The relationship between TRDM and resilience will be mediated by changes in the adolescents' friendship networks.*
    - *Hypothesis 3a: TRDM will be negatively associated with the change in deviant peer proportion.*
    - *Hypothesis 3b: The change in deviant peer proportion will be negatively associated with resilience.*
    - *Hypothesis 3c: The indirect effect of TRDM through the change in deviant peer proportion on resilience will fully or partially explain the direct protective impact of TRDM.*

My results overall do not support Hypothesis 3a. Some sensitivity analyses of the interaction models found evidence that TRDM in 7th grade reduced the deviant peer proportion in 8th grade; the multigroup analyses suggest that this was largely driven by a reduction for those with low deviant peer exposure. Turning to the multigroup models, those all deviant peer exposure in 9th grade (and mid deviant peer exposure in 8th grade in the model with no LDV) tended to reduce their exposure in the next wave if they had higher TRDM. However, in several models, TRDM leads to a significant *increase* in the deviant peer proportion at the next wave. The interaction analyses indicate that for younger adolescents (at the first two waves), higher TRDM, when paired with higher levels of deviant peer exposure, leads to increases in the deviance of their friend group at the next wave. The multigroup models find TRDM

to be associated with a higher proportion of deviant peers for those with mid deviant peer exposure in 6th grade and high deviant peer exposure in 8th grade. Given the countervailing results, I cannot state that higher TRDM is linked to making prosocial changes to one's friend group.

Hypothesis 3b is clearly supported by my results. Both the interaction and multigroup models find an increase in deviant peer proportion to decrease the likelihood of resilience (or, for those with an entirely deviant peer group, a decrease in the deviant peer proportion to increase the likelihood of resilience). This effect maintains the same direction across all waves and levels of deviant peer exposure (though it sometimes has no significant effect). But, given the lack of support for Hypothesis 3a, it is unsurprising that there is limited evidence of an indirect effect of TRDM through a change to the deviant proportion of the friend group (Hypothesis 3c). There is some evidence of an indirect effect in the interaction models starting in 7th grade, where high TRDM leads to a slight decrease in the change to the deviant peer group for those with low deviant peer exposure, but not for those with high deviant peer exposure (see Figure 8). Some multigroup models also find evidence of a positive indirect association with resilience for TRDM for those with low DP exposure in 7th grade. However, there is also a negative indirect association of TRDM with resilience for those with high DP in 8th grade. Overall, the results are inconsistent and sensitive to model specification, providing very limited support for Hypothesis 3c. Importantly, the direct impact of TRDM on resilience was never reduced in magnitude or statistical significance, indicating overall no support for TRDM's partial or full mediation through prompting change to adolescent's

friendship networks. Thus, I conclude there is no evidence for Hypothesis 3c and Hypothesis 3.

Table 32. Summary of Results for Interaction Models

	TRDM	DP Prop	Interaction	Δ DP Prop	TRDM -> Δ DP Prop	Interaction -> Δ DP Prop	TRDM Indirect Effect	Interaction Indirect Effect
6th – 8th	+	-	NE	-	NE	+	NE	-
7th – 9th	+	-	NE	-	NE/-*	+	+	-
8th – 10th	+	-	NE	-	NE	NE	NE	NE
9th – 11th	+	NE	NE	-	NE	NE	NE	NE

DP refers to Deviant Peers. Δ signifies change. Interaction refers to the interaction term between TRDM and the deviant peer proportion. All estimates that were not statistically significant (not including marginal significance at $p < .10$) are listed as NE. *This estimate differed in sensitivity analyses; the models that included only serious delinquency and that used a maximum likelihood estimator found TRDM to be associated with a decrease in the proportion of deviant peers (-).

Table 33. Summary of Results and Equality of Coefficients Tests for Multigroup Models

	TRDM			Δ DP Prop			TRDM -> Δ DP Prop			TRDM Indirect Effect		
	Main	No LDV	Serious Only	Main	No LDV	Serious Only	Main	No LDV	Serious Only	Main	No LDV	Serious Only
6th – 8th												
Low DP	+	+		-	-	-						
Mid DP		+		-	-	-	+		+			-
High DP	+*	+*		-	-	-						
All DP					-							
7th – 9th												
Low DP				-	-		-	-	-	+	+	
Mid DP	+	+	+*	-	-	-						
High DP	+*	+*		-	-	-						
All DP												
8th – 10th												
Low DP	+	+	+	-	-	-						
Mid DP	+	+		-	-	-		-				
High DP	+	+	+	-	-	-	+	+	+	-		
All DP	+	+	+*	-	-			-				
9th – 11th												
Low DP		+			-							
Mid DP		+	+		-	-						
High DP		+		-	-							
All DP						-	-	-	-			

DP refers to Deviant Peers. Δ signifies change. LDV refers to a lagged dependent variable. All estimates that were not statistically significant (not including marginal significance at $p < .10$) are listed as blanks. * denotes that for this group of DP exposure, TRDM's estimate is the largest and significantly differs at $p < .10$ from estimates of other groups in the same wave using a Wald χ^2 test of equality of coefficients.

CHAPTER 5: DISCUSSION

Over a century of research has found deviant peers to be related to crime (Akers et al., 1979; Breckinridge & Abbot, 1912; Pratt et al., 2010; Shaw & McKay, 1942), an association that is especially large during adolescence (Steinburg & Monahan, 2007; Warr, 2002). Given the consistent and strong relationship, it is unsurprising that many theorists, including Sutherland himself, have used causal or deterministic claims to discuss the influence of others on criminal behavior (Sutherland et al., 1992; Sutherland & Cressey, 1960; Warr, 2002). Yet, it is important to theoretically and methodologically acknowledge heterogeneity in the outcomes of exposure to deviant peers. Assuming all adolescents with deviant peers will become delinquent is not only a logical fallacy, but also limiting to theory and practice. It implies that adolescents cannot chose to act with agency in ways that may be inconsistent with their friend groups yet consistent with their long-term goals and preferences. It also is inconsistent with interventions designed to disrupt the position or influence of deviant peers in adolescents' social networks.

Adolescents who avoid delinquency in the face of deviant peer influence can be said to display resilience, or positive adaptation in the face of adverse circumstances associated with a specific negative outcome (Fergus & Zimmerman, 2005; Luthar, 2006). These adolescents should be of great interest to researchers, as they are able to avoid a strong risk factor that leads others to negative outcomes. One internal factor that may contribute to resilience to deviant peer influence is thoughtfully reflective decision-making skills (Paternoster & Pogarsky, 2009). TRDM may have a direct impact on resilience that is promotive (helpful at all levels

of deviant peer exposure exposure) and/or protective (becoming more important at higher levels of exposure). TRDM may also have an indirect impact on resilience through prompting positive change in adolescent's friendship networks, which in turn influences later resilience (Paternoster et al., 2011). In this dissertation, I investigate these direct and indirect pathways of TRDM.

Major Findings

My first notable finding is that resilience to deviant peer influence is found in adolescence, even amongst individuals with a highly or entirely deviant peer group. A little over half of the sample demonstrated resilience, though this varies by level of deviant peer exposure and age. Overall, the "negative cases" are many (Sullivan, 2011). This aligns with the research findings that spurred an academic focus on resilience: many high-risk youths still have good outcomes (Garmezy, 1973). That is not to say that adolescents with deviant peers may not experience poor outcomes in other domains of life, but, in this sample, over half avoided delinquency 1-2 years after exposure to deviant peers. This is encouraging on a practical note; academically, there is a need for theory and research to explain the "missing links" that explain the differences between an outcome of resilience or delinquency.

This acknowledges that individuals can act with agency and are not merely acted upon by their external environment, even in the case of deviant peer influence (Akers, 1990). Adolescents may not normatively adopt the definitions of their deviant peers, even when exposed to a high degree (Matza, 1964). This could also represent a lack of socialization of delinquent values from peer to adolescent. Matza (1964) argued that adolescents generally hold unfavorable views towards delinquency, even

if they do deviate. In contexts favorable towards delinquency, they may instead use neutralizations to temporarily excuse behaviors inconsistent with conventional norms (Sykes & Matza, 1957). Adolescents' peers may "drift" in and out of delinquency according to their context without adopting a delinquent value system (Matza, 1964); thus, adolescents could receive many definitions unfavorable to delinquency even from deviant peers. While this dissertation used objective indicators of peer deviance, future research should examine whether the results change when measuring peer deviance by adolescents' perceptions of their peers' behavior.

Second, TRDM is consistently positively related to resilience. This suggests that TRDM acts as a promotive factor by decreasing the likelihood of delinquency. Th impact of TRDM on delinquency for the 9^{th} – 11^{th} grade group appears to be less strong – it appears in the models that exclude the LDV, but not those that include prior delinquency. It may be that TRDM is most important for resilience at the younger waves, when decision-making skills tend to suffer the most, especially when paired with peer effects (Gardner & Steinberg, 2005; O'Brien et al., 2011; Steinberg & Cauffman, 1996). This is important as all the adolescents in this study were exposed to deviant peers. Even when faced with this risk factor, TRDM could prevent delinquency; standardized coefficients demonstrated that TRDM's positive effect eclipsed the negative impact of deviant peers in most direct interaction models (all except the last wave, where TRDM was less impactful).

Although TRDM is intended to be an operationalization of agency (Paternoster & Pogarsky, 2009), concluding that TRDM's impact on resilience is due to agentic action still makes assumptions. I cannot exclude the possibility that TRDM

is developed through one's environment acting upon the adolescents. For example, it may be that TRDM is encouraged by good parenting strategies, a stable environment, and social support from many conventional others. Though TRDM maintains significance with the addition of some controls of environment, I may have been missing important features that could mask the true origins of TRDM's prosocial impact. Future research should thus evaluate the external factors that promote development of TRDM. Additionally, it may be that for many of those with TRDM, the "rational" action is to not offend, but that is not necessarily true for all. Environmental context still exerts an impact by shaping what behaviors are learned, adaptive, and rational during decision-making processes (Rivers et al., 2017).

Third, the interaction models did not provide evidence for a linear interaction between TRDM and deviant peer influence. This differs from the results of prior research. Particularly, it differs from the results of Thomas and McGloin (2013) and Fergusson and colleagues (2007), who find that there is an increased impact of deviant peer influence on delinquency for those with low impulsivity or novelty-seeking, respectively. This provides more support for the theoretical and empirical evidence that impulsivity and TRDM are independent constructs which interact with environmental risk factors in different ways. Importantly, it also differs from the results of Botvin and colleague's (1998) study, which found evidence that the deviant peer effect reversed itself for adolescent drinking behaviors, as well as Gardner and colleague's (2008) and Goodnight and colleague's (2006) finding that deviant peers were less impactful for those with more self-regulation or lower reward dominance, respectively. These studies measured constructs more analogous to TRDM, and I

expected my results to resemble these; however, I did not find similar evidence of prosocial linear interactive effects for TRDM.

However, it is important to note that my study differed in from prior work in several important ways, which both distinguishes my dissertation from prior work and likely contributes to its differences from prior findings. One such factor is in my exclusive focus on adolescents who have been exposed to deviant peer influence. The processes at work for adolescents who are social isolates or who have entirely non-deviant peer groups may very well differ; the current study avoids inferring that the behavior of adolescents with many deviant peers will necessarily be the opposite of those with none. Second, my sample was comprised of adolescents attending rural and semi-rural schools. Rural communities tend to have strong parental monitoring and strong social norms against deviant behavior (Marsden & Srivastava, 2012; Smith, 2003), which may help explain the seemingly high rates of resilience to deviant peer influence. Third, I measured resilience, or the absence of all delinquency, rather than focusing on whether it increased or decreased the level of adolescents' delinquency. Under these conditions, TRDM appear promotive, but not especially protective at the highest level of deviant peer exposure.

Fourth, the multigroup models told a different, but more complicated, story – one that shows that TRDM does have a greater impact on resilience at higher levels of deviant peer exposure. The estimates of TRDM's effect were largest in magnitude and most consistent for adolescents exposed to a high (or occasionally mid) level of deviant peer influence – yet, for most waves of analysis, TRDM does *not* impact resilience for those who have entirely deviant peers. Overall, the effect here appears

nonlinear, where adolescents with substantial exposure to but not only deviant friends experience the greatest benefits from TRDM. These results, to some extent, support the idea that TRDM serves as protective factor, or a factor that is especially helpful for those at a high level of the risk factor. Thus, these results are not in fact altogether different from Gardner and colleague's (2008) and Goodnight and colleague's (2006) studies that find a heightened impact of reward dominance or self-regulation at a higher level of deviant peer exposure, though the effect is non-linear in my sample for TRDM.[27] TRDM is both promotive of resilience and protective at high levels of the risk factor and can aid our explanation of these "negative cases" that have deviant peers but avoid delinquency.

My findings still differ from the results of studies examining susceptibility according to impulsivity and novelty-seeking (Fergusson et al., 2007; Thomas & McGloin, 2013). This is not surprising for a few reasons. The constructs with conflicting results tend to be focused on the pull of the here and now. While those with high TRDM may experience the pull of the here and now, they should be able to resist this pull if it would lead to undesirable outcomes. Accordingly, TRDM tends to be operationalized with different measures. In this dissertation, I control for impulsivity, which is found empirically distinct from TRDM, in order to isolate the impact of TRDM on resilience. Moreover, while many decision-making styles are theorized to be value-neutral, meaning one can reach a "good" or "bad" decision both with or without them, TRDM assumes that those who engage in this thinking style are

[27] I cannot compare the results of the multigroup models to Botvin and colleague's (1998) study; while they split the sample by level of decision-making skill, I split the sample based on level of deviant peer influence. While I can make comparisons for the continuous interaction models, which can be interpreted in either direction, my multigroup models are not comparable to this study.

more likely to come to a decision that will have long-term positive implications. This was true in my study, where TRDM helped to ameliorate the risk posed by high exposure to deviant peers. My findings that TRDM is promotive and protective regarding resilience to deviant peer influence are consistent with research demonstrating the power of self-regulation and good decision-making skills in dampening the typical impact of deviant peers (Gardner et al., 2008; Goodnight et al., 2006). Though these constructs still differ from TRDM, they resemble it more closely in that they involve goal-oriented behavior that is not disrupted in the face of appealing rewards – thus, adolescents can resist the social and personal rewards offered by delinquency in the context of deviant peers.

Typically, protective factors are most impactful for those at the very highest level of the risk factor. The finding that TRDM was not consistently impactful for adolescents with all deviant peers is thus curious. Arguments from the challenge model of resilience may apply, where adolescents at the lowest and highest levels of the risk factor may be most susceptible to its influences – the lowest, because they lack coping mechanisms and are least equipped to handle the risk factor, and the highest, because this level of the risk factor can overwhelm any coping mechanisms they possess (Fergus & Zimmerman, 2005; Garmezy et al., 1984). This is consistent with other researchers' observations that youth residing in moderately stressful environments can experience various positive outcomes (Christiansen & Evans, 2005; Ellis et al., 2005; Mortimer & Staff, 2004), highlighting the positive adaptation and "hidden talents" that can form under adversity (Ellis et al., 2017; Frankenhuis et al., 2020).

In the challenge model, the risk factor is typically the same as the protective factor (i.e. being exposed to a moderate amount, not a low or high amount, leads to positive or at least not as negative outcomes; Fergus & Zimmerman, 2005). Yet, integral to this perspective is the argument that adolescents at a moderate level of risk learn how to cope with and overcome the risk factor at hand, which implies the development of other constructs to increase resilience. In this dissertation, I directly measure that phenomena, finding that in the context of a moderate amount of risk factor, adolescents use another protective factor (TRDM) as a coping skill to overcome deviant peer influence. The challenge model (or inoculation model) is typically tested using longitudinal growth modeling of the risk factor (including a polynomial term), often examining whether youth who overcome low levels of risk at younger ages later become more competent under moderate risk in later years (Zimmerman et al., 2013); future research should use these methods to investigate the possibility that deviant peer influence operates in this manner.

Moreover, arguments from Sutherland's (1947) and Aker's (1973) theories likely apply here. The principle of differential association places great weight on whether messages favorable to delinquency *outweigh* those unfavorable. When one's peer group is largely non-deviant, as is the case for the low-level of exposure group, there is less ambiguity about the acceptable course of action, and TRDM may not be as necessary to avoid delinquency. For those with mid degree of peer exposure, adolescent's peers send mixed messages about the acceptability and utility of deviant acts. TRDM may aid long-term decision-making for this group. It is strange that TRDM is most impactful at a high degree of deviant peer exposure, where there

should not be as much ambiguity as is present at the mid-level. However, it is reasonable to assume that adolescents are still receiving messages unfavorable to delinquency from adults at school, afterschool programs, in the home, and even perhaps from deviant peers (Matza, 1964); thus, even with this high degree of exposure, there may still be a good deal of ambiguity. When youth's peer groups are entirely deviant, however, this ambiguity may be reduced to a level where adolescent's decision-making skills no longer increase or decrease the likelihood of resilience. It may thus be that TRDM is helpful in discerning between a deviant and non-deviant course of action when there is a great deal of ambiguity, but less so when the accepted course of action is clear.

However, for the set of multigroup analyses conducted when adolescents were in 8th – 10th grades, I find conflicting results.[28] TRDM is most protective at the highest level of deviant peer exposure – all deviant peers – at the age where deviant peers are both very likely and at the height of their influence (although, it only exceeds other groups in a statistically significant manner in models of only serious delinquency). At these grades, adolescents tend to be aged 13-16, the exact ages at which deviant peer influence is at its peak (Steinberg & Monahan, 2007). Resilience amongst adolescents with entirely deviant peers indeed noticeably dips in descriptive analyses for this set of waves (see Figure 5). If the pull of deviant peers is so strong at these ages, and adolescents with all deviant peers have the strongest pull towards delinquency, why then would TRDM be especially impactful in this group?

[28] Though I do not explicitly test for age-related differences, conducting multiple analyses across waves lends itself to discerning some differences by age. Future research should consider growth modeling or similar statistical techniques to examine change in deviant peer influence, TRDM, and their interaction over time.

These ages represent an important time in adolescents' lives for a few reasons: an increased risk of associating with deviant peers, an increased impact of deviant peer influence, and a school transition – namely, the transition from middle to high school. Researchers have theorized that school transitions can disrupt friendship ties and social support, as adolescents are exposed to new peers and may have less routine contact with their old friends (Berndt, 1989; Fenzel, 1989). There is some evidence to support that even normative school transitions can disrupt friendship networks (South & Haynie, 2004). This may be especially true for rural youth, where youths may have been in classes with the same group of students until transitioning into a larger high school. In the PROSPER data, adolescents who transition to a different school receive less friend nominations from their peers and are less central to peer networks (Felmlee et al., 2018). This is yet another reason why adolescent's ties may be a priority to them at this age.

This age paired with this transition likely carries an increased risk of associating with deviant peers. The deviant proportion of adolescents' peer groups increase around 8^{th}-9^{th} grade, and adolescents may also find that previously non-delinquent friends change their behavior at the beginning of high school. Yet, when things become more likely, they tend to become more "normal" – and exposure to deviant peers may become less nefarious as "adolescent limited" offenders associate with and mimic the behavior of their "life course persistent" peers (Moffit, 1993). It may be that youth not particularly at a high-risk in other ways or waves can end up with an entirely deviant peer group at this stage, but, with well-developed coping skills, are able to buffer their influence. This age group is particularly vulnerable to

risky decision-making when around peers (Gardner & Steinberg, 2005), and adolescents who depart from the norm by engaging in TRDM even with all deviant peer influence may be especially protected even at the highest level of exposure. Future research should investigate these developmental pathways.

The last major conclusion I draw from this dissertation relates to a finding that does not significantly differ from the null; I do not find enough evidence to support my contention that TRDM has an indirect impact on resilience through prompting change to the deviance of adolescents' social networks. A decrease in the deviant proportion of the friend group from one wave to the next does increase the likelihood of resilience, according to expectations. Sensitivity analyses showed that changing friendships, including the selection of new friends, was associated with a great deal of change to the adolescent's deviance at the next wave. However, evidence of TRDM's role in prompting change to the deviance of one's friend group was inconsistent. This corresponded to little evidence of an indirect effect of TRDM on resilience and no support for full or partial mediation of its direct role in prompting resilience.

One explanation may lie in the contention that adolescents do not have complete control over the friends they select; not all schoolmates will reciprocate attempts to become friends, and adolescents may "select" the friends that are available or are already connected to them through the dense, cohesive peer groups that can form in school settings. Giordano and colleagues' (2004) description of successful former offenders selecting more positive friends was not a sample of youths, but adults. Given the primacy of peer rejection in adolescence, most adolescents would likely rather keep friends that are different from them than become

social isolates, who often suffer other negative consequences (DeMuth, 2004; Kreager, 2004). For example, McGloin (2009) found the behavior of adolescent friends that differed on delinquency began to "balance" over time, rather than the adolescents severing the ties. Another related explanation may be how common deviance becomes during adolescence (Haynie, 2002); finding non-deviant friends at all (or non-deviant friends that stay non-deviant over the course of a year) may become increasingly hard to do as adolescents reach high school age. Adolescents may even recognize the temporary rebellion of many peers' deviance (Moffit, 1993), inferring that deviant behavior in otherwise well-adapted adolescents may not be likely to continue. Overall, friendship choices may be less agentic than I originally theorized, and TRDM may not be of much assistance in navigating the complicated world of adolescents' changing friendships.

Limitations

My study's sample and analytic framework present limitations. First, PROSPER Peers is not a nationally representative sample; rather, the dataset was gleaned from twenty-eight majority-white rural and semi-rural communities in Iowa and Pennsylvania. As researchers of processes of peer influence tend to utilize metropolitan or nationally representative samples, it is certainly beneficial in criminology to test hypotheses in a rural/semi-rural sample. Yet, the current study will not have generalizability outside of these communities, and future research should examine whether my findings replicate in other contexts. Additionally, the PROSPER data underrepresents adolescents from smaller school districts (due to enrollment requirements to be included in the sample) and minority (especially black)

youth living in rural communities. The results thus may not generalize to students from smaller rural school districts and black rural/semi-rural students.

Second, the present study also removes all individuals who did not report matchable friendship nominations and adolescents whose matchable friends did not display any deviance. It was necessary to remove adolescents without exposure to deviant peers in order to appropriately study resilience, which definitionally requires exposure to the relevant risk factor. Excluding those who do not have friends is necessary to study the questions at hand, but excluding those who do have friends but did not report them does limit generalizability. There is no way to distinguish the two in the current data. I also cannot distinguish those who do not have deviant friends to those who do, but this information was missing from the friends' reports.

Social isolates and adolescents with non-deviant friend groups are not part of my population of interest and excluding them from the sample is consistent with other research on peer networks (Kreager et al., 2011). However, this does limit generalizability in that we cannot assume that the relationships identified in this study will that impact delinquency in social isolates and adolescents with non-deviant peer groups in a similar fashion. Social isolates especially tend to differ from other adolescents in many meaningful ways (Kreager, 2004). It is worth noting that most adolescents would be exposed to deviant peers and thus included in my sample at some point across the four starting waves.

Third, although a strength of the current study is its ability to match friendship nominations to surveys and have objective indicators of friends' delinquent behaviors, PROSPER Peers cannot accommodate out-of-school, or even out-of-grade,

friendships. Almost all adolescents in these small towns do, however, attend the nearest school, enhancing the probability that the friendship nomination data does still capture a large proportion of adolescents' friends (Bielick & Chapman, 2003; Osgood et al., 2013b). School friends may be especially important to rural youth, who have more geographic distance limiting their exposure to similarly-aged peers. This could still be a weakness, however, as delinquent adolescents may be more likely to make friends outside of school (Claes & Simard, 1992). Delinquent adolescents do tend to have more friends overall, so it is unclear how exactly out-of-school/grade friendships would impact their in-grade social ties. Future research using perceived peer deviance to test these hypotheses can ameliorate some of these concerns.

Another potential limitation of my study is a potential failure to adequately control for the interdependencies in the network. Processes of peer influence and selection in networks are statistically complex to estimate; researchers have argued that certain methods need to be utilized in order to appropriately control for statistical dependence (i.e. interdependencies) of these influences, which are often reciprocal, simultaneous, and indirect (Osgood et al., 2013b; Veenstra & Dijkstra, 2011). Moreover, there are concerns that peer influence and/or selection will be overestimated in studies that do not adequately control for these phenomenon (Ragan et al., 2019). Approaches to controlling for interdependencies include the Simulation Investigation for Empirical Network Analysis (SIENA) software developed by Snijders and colleagues (Snijders, 2001, 2005; Steglich et al., 2010). SIENA has been suggested as a remedy for these concerns as it simultaneously accounts for network processes of selection and influence, including the tendency for adolescents

to befriend and be influenced by others that they are connected to in the network. Using SIENA was not appropriate for my analysis, which focused on a certain population (i.e. those who have deviant peers) rather than the behavior of the entire network; however, concerns about overestimating peer influence when using conventional approaches instead of SIENA may be unjustified (Ragan et al., 2019).[29]

In these analyses, I do take measures to avoid misestimating peer influence and selection. First, my study directly measures the behavior of adolescent's entire network of up to 7 friends. Given that most adolescents (about 65% in my sample) did not nominate all 7 possible friends, the captured networks are likely good measures of adolescents' school-based friendship networks. Second, my study includes a strict control for selection by including the lagged dependent variable. By using a cross-lagged longitudinal design, I am able to capture processes of both selection of influence by measuring the impact of both individual and peer network behavior on both changes in the peer network and changes in individual behavior (see Veenstra & Dijkstra, 2011). However, my study cannot control for changes that occur in the network between the measured annual waves. My study also does not measure transitivity, or the increased likelihood of friendship amongst adolescents with a shared friend in previous waves, which could inaccurately attribute the friendship selection to shared behavior (Veenstra & Dijkstra, 2011).

[29] Ragan and colleagues (2019) used the same PROSPER Peers data with discrete, ordinal outcomes (including delinquency) to assess whether conventional regression approaches (compared to stochastic actor-based modeling using SIENA) led to biased estimates of peer influence and selection. Compared to conventional regression approaches that controlled for the outcome of interest at a previous wave, Ragan and colleagues (2019) instead found estimates of peer influence to be larger in the SIENA models, concluding that their findings "dispel the notion that SIENA, which uses a method that takes into account network complexities of the influence process, produces more conservative peer influence estimates" (p. 30).

Additionally, my study measures delinquency, both of the adolescent and the adolescent's peers, using self-report measures. Self-report data is well-accepted in criminology, where "official" measures of delinquent behavior are constrained by the likelihood that crimes are detected and, for measures of individual offending, solved by the appropriate criminal justice agency. This represents the "dark figure" of crime – the majority of crimes go unreported or unsolved and thus do not appear in official reports. Additionally, arrest and conviction are not equally likely for all persons who have offended, but depends on personal and environmental characteristics, and thus official reports will differ for certain groups (i.e., Matsueda et al., 1992). The advent of self-report measures changed criminologist's perceptions of who was committing crimes and where and, as such, they are considered to be our current best source of longitudinal data about crime (Thornberry & Krohn, 2011). Self-report measures are additionally found to be adequately valid and reliable (Hindelang et al., 1981; Huizinga & Elliott, 1986). However, memories are still fallible, and crime is still a sensitive topic; individuals can forget behaviors (especially for longer response periods) or mislead researchers due to fear of the consequences should their deviant behavior be exposed (Huizinga & Elliott, 1986; Thornberry & Krohn, 2000). Exposure of delinquent behavior can be even more detrimental in rural environments, where such behavior is typically seen as a large threat and formal or informal sanctions can be large (Weisheit et al., 2006). Thus, it is possible that delinquency was underreported in my sample, which would imply less resilience in reality.

Using SEM also comes with certain limitations. First, all the analyses that will be presented are confirmatory, not exploratory. That is, SEM will not search for the

best model specification, but will instead be able to confirm or disconfirm whether the existing, proposed model is a good fit and the direction and significance of the specified pathways. The model needs to be specified using existing theoretical and empirical knowledge of the subject at hand. It assumes that the researcher knows the underlying structure of the model before it is tested. As a result, the models are vulnerable to misspecification. The model is sensitive to omitted variables, and these biases are not detected unless the variables can be included in model and the researcher can test for which model fits best. The models also make other assumptions about the properties of the data – for example, that the included variables are not subject to multicollinearity and display multivariate normality. For some models, violations of multivariate normality have relatively benign consequences; for others, robust chi-square, standard error, and fit indices can improve estimation (Hancock & Wasko, 2010).

Missing data may create some bias in estimations.[30] The weighted least squares estimator necessitates using pairwise deletion for missing observations. Pairwise deletion includes each pair of variables from each case for which the data is available, regardless of whether the entire set of variables is available. Not deleting all cases with any missing variables from the model does include more cases and thus

[30] Importantly, the current analysis cannot fully disting**u**ish missing data on friendships from the lack of friends (see also footnote 13 on page 64); both would be excluded from the analyses, but those who do not have friends would not be truly "missing" this value. Individuals who nominated friends that cannot be matched using school records or matched to friends that did not report any information about delinquency were excluded as well. Thus, although there is no missing data on number of friendship nominations or the proportion of an adolescent's friend group that displays deviance, this is because the sample selection procedure systematically excluded these students from the analyses.

improve power over using listwise deletion, but it still does not maximize the amount of information that can be drawn from each case.

Pairwise deletion also assumes that missing data are missing completely at random (MCAR), which is likely not true for these variables in the given sample. Missing data can be missing completely at random (MCAR), where missing values of a variable do not depend on its unobserved values or other variables, missing at random (MAR), where missing values of a variable do not depend on its unobserved values, but may be related to other observed values in the data, or missing not at random (MNAR), where missing values depend on its unobserved values, a fundamentally untestable assumption (Rubin, 1976). Little's (1988) MCAR test finds that the missing data amongst the variables used in these analyses are not MCAR [$\chi^2(1386) = 6516.66$, $p = .000$], questioning whether the missing data biases results using the weighted least squares estimator. The direction and magnitude of these biases will be unobservable if data are MNAR. However, researchers have found the robust weighted least squares estimator found in Mplus (WLSMV) to produce efficient, unbiased estimators under conditions wherein missing data is handled using pairwise deletion (Asparouhov & Muthén, 2010).

In structural equation modeling, full information maximum likelihood (FIML) is commonly used to handle missing data, yet this approach cannot be used with a weighted least squares estimator. FIML allows researchers to estimate models using all available data, not just the complete cases or pairs of variables. Maximum likelihood (ML) models attempt to find the population parameters that are most likely to explain the observed data and adjusts the likelihood function so that each case

contributes the maximum amount of information possible.[31] No data are ever imputed, but all available information is used. Cases that do include missing data will still contribute less to the parameter estimates. Yet, it has been demonstrated to produce unbiased estimates if data are MAR or MCAR (Cham et al., 2017). As such, I used FIML to accommodate missing data in the sensitivity analyses using maximum likelihood estimators and found similar results to my main models.

A final limitation lies in the lack of establishing true causality. Although SEM is intended to model causal relationships between variables, causality is established by design, not modeling approach, and this dissertation does not include an experimental intervention. Though the current study can establish associations between variables, include control variables, and establish temporal ordering, it cannot rule out the role of other unobserved variables and thus cannot identify true causal effects.

Conclusions and Future Research

Despite these limitations, this dissertation moves the field forward in several important ways. As the results pertain to theory, this dissertation takes several steps forward. The questions asked in this dissertation differs from those typically asked in the literature on deviant peer influence. Namely, I ask for whom deviant peers do not seem to matter and why this would be the case. There is a need for this body of literature to ask new questions about deviant peer influence (McGloin & Thomas,

[31] A weakness of this approach is that the sample size of the analyses can be confusing – specifically, it is unclear whether it is appropriate to include each person when for some persons we don't observe all variables that contribute directly to the estimates.

2019), and these questions help to fill that gap. Focusing on resilience to deviant peer influence acknowledges the heterogeneity in this risk factor (Rutter, 2006). The focus on the internal asset of TRDM also moves conceptions of social learning theory closer to Aker's (1990) intended "soft behaviorism," which allows for the role of agentic choice. Additionally, in the field of resilience, it is important to acknowledge the ways in which personal assets and environmental resources interact rather than studying them separately or even pitting the two factors against each other. It is hypothesized that some of the most impactful links to resilience may stem from factors that interact with or trigger positive changes to one's environment (Liebenberg & Ungar, 2009; Masten & Obradović, 2006).

As these results pertain to policy, identifying a way to encourage resilience to deviant peers in adolescence can mitigate a great deal of antisocial behavior – beneficial for both the adolescents and society. It is clear that TRDM indeed increases the likelihood of avoiding delinquency, even in a sample that was entirely exposed to deviant peers. Given consistent exposure to deviant peers in schools, neighborhoods, and activities, it may be difficult (if not impossible) for policies or programs to eliminate deviant peer influence in the lives of many adolescents. Programs that attempt to alter the selection into peer friendships or provide tools to boost resilience in the face of deviant peer influence are thus a more practical and effective choice. Given my results, interventions that boost TRDM should likely not be used to attempt to reduce the importance of deviant peers in adolescents' social networks, though other intervention programs have shown to be effective in this manner (Botvin & Griffin, 2004; Osgood et al., 2013a).

Yet, according to my results, programs designed to foster TRDM could increase the likelihood of resilience, especially for adolescents with mid to high levels of deviant peer exposure. If TRDM is indeed a factor promotive of resilience, how we increase TRDM in adolescence is an area ripe for future research. Paternoster and Pogarsky (2009) viewed TRDM as something malleable over time, both due to natural human development and interventions, and something that could be taught using techniques developed in behavioral economics and cognitive behavioral theory (see Ramsay & Rostain, 2008; Thaler & Sustein, 2008).

Interventions that promote good decision-making are often found to foster resilience to a wide variety of risk factors. For example, teaching life skills, which includes problem-solving and decision-making skills, can mitigate risk (Henderson & Milstein, 2003). Integrating social competence enhancement into school curricula, in programs such as Responding in Peaceful and Positive Ways (RIPP; Farrell et al., 2003) and Providing Alternative Thinking Strategies (PATHS; Greenberg et al., 1995), is also likely to decrease behavior problem rates. Heller and colleagues (2017) used cognitive behavioral therapy (CBT) in the Becoming a Man (BAM) program to find a significant reduction in violence for high-risk youth in the program and, after examining the possible mechanisms behind this change, found that it could be attributed to increased time spent making decisions. Programs such as these can likely improve TRDM skills; other "naturally occurring" factors in adolescent's environment that can increase or reduce TRDM should also be identified. It is necessary to first "understand the origins of good decision-making" before designing specific interventions (Paternoster et al., 2011, p. 21).

Thus, researchers, practitioners, and policymakers should work together to investigate ways to promote TRDM. Additionally, I recommend several other avenues for future research based on my aforementioned findings, arguments, and limitations. First, given my finding that TRDM did not have a consistent significant impact on the deviant peer composition at the next wave, factors that do prevent adolescents from choosing deviant friends should be further explored. They are of both theoretical and practical importance. Second, given that this sample was primarily rural, a test of resilience to deviant peer influence in an urban or nationally representative sample would lead to further understanding of the generalizability of my findings. Particularly, testing similar models in contexts where deviant friends (and definitions) are more common, social networks are less dense, and parental and community monitoring suffers could show different results.

Third, explicitly testing for differences in these processes by age will further illuminate the developmental processes at work, both social and cognitive. Using longitudinal growth models could illuminate whether adolescents develop coping skills (including TRDM) after exposure to low levels of the deviant peers at an early age (i.e. challenge model; Zimmerman et al., 2013). Special attention should be given to grades 8-10, as my results for this age group differed; factors such as cognitive and social development, change in exposure to deviant peers, and the transition to high school should be explored. Fourth, studying these factors in the context of methods that analyze the entire network, such as SIENA, may shed light on some of the more complicated and recursive processes at work. These analyses could account for change in friendship networks and behaviors beyond the assumption that each is

entirely driven by the "ego" (the individual being analyzed). Fifth, measuring deviant peer exposure with adolescents' *perceived* peer deviance (rather than objective, as in my study) could examine whether adolescents recognize their friends' delinquency (and are receiving deviant messages, contrary to Matza, 1964) and could provide a way to include out of school/grade friendships.

Finally, future research should further examine the interaction between internal assets and environmental factors. In this dissertation, I found evidence of non-linear interaction between the external predictor of deviant peer exposure and TRDM, providing further support for these claims. Yet, this is not the only feature of one's environment that likely interacts with decision-making constructs to predict resilience among those at high-risk for crime. Other risk factors may have cumulative impacts or beget others – for example, poor environment or parenting leading to more exposure to deviant peers or an early arrest or suspension cutting off prosocial peer groups – and these risk factors likely interact in complex ways to impact resilience.

For example, I observed parental monitoring to make a clear contribution to resilience across all waves and levels of deviant peer exposure and, in conjunction with parental relations, to lessen the deviant peer proportion at the next wave. Beyond parental monitoring predicting exposure to deviant peers and delinquency, there is empirical and theoretical justification for peer influence (Mrug & Windle, 2009) and decision-making factors, including short-term mindsets (van Gelder et al., 2018), to be mediated or moderated by parenting practices. I found low SES, on the other hand, to decrease the likelihood of resilience and increase deviant peer exposure at the next wave. Poor environment and socioeconomic status can indeed increase exposure to

deviant peers and alter decision-making in ways that make short-term rewards appear more appealing (Fenneman & Frankenhuis, 2020; Rivers et al., 2017; Sturge-Apple et al, 2016). These interactional pathways and others should be a focus of further investigation. I hope that future researchers will continue to focus on the "ordinary magic" of adolescents who are able to resist the pull of deviant peers and other important risk factors due to the interaction of personal assets and environment.

Appendix A: Pooled Sample Descriptive Statistics by Resilience

Table A1. Pooled Sample Descriptive Statistics by Resilience

	Resilience		*No Resilience*	
	Mean or %	SD	Mean or %	SD
Δ DP Proportion[b]	-.05	.32	-.02	.34
DP Proportion	.47	.25	.54	.26
TRDM	.23	.88	-.18	.94
Prior deviance	23.82%	--	61.31%	--
Male	44.73%	--	55.67%	--
White	88.39%	--	85.70%	--
Free Lunch	-.53	1.55	-.25	1.65
Parental Monitoring	4.46	.63	4.11	.75
Parent Relations	.05	.39	-.11	.41
Impulsivity	2.43	1.23	2.83	1.19
UUS	6.91	2.97	7.25	2.85
# of Nominations	5.42	1.69	5.26	1.74
Tx Condition	44.08%	--	41.11%	--
N (%)	10,993 (56.03%)		8,628 (43.97%)	

DP refers to Deviant Peers. UUS refers to unsupervised, unstructured socializing. Δ signifies change.
[b] Measured at Time 2.

Appendix B: Direction and Significance of Control Variables from Main Models

Table B1. Direction and Significance of Control Variable Effects Predicting Resilience and Change in Deviant Peer Proportion in Interaction Models

	Predicting Resilience				Predicting Change in Deviant Peer Proportion			
	$6^{th} – 8^{th}$	$7^{th} – 9^{th}$	$8^{th} – 10^{th}$	$9^{th} – 11^{th}$	$6^{th} – 8^{th}$	$7^{th} – 9^{th}$	$8^{th} – 10^{th}$	$9^{th} – 11^{th}$
Prior Deviance	-***	-***	-***	-***	+***	+***	+***	+***
Male	-†	-†	-***	-***	+***	+***	+***	+***
White						-*		
Free Lunch	-***	-***	-**		+***	+***	+**	+*
Parental Monitoring	+**	+***	+**	+***	-**	-***		
Parental Relations			+**		-†		-*	-*
Impulsivity		-**	-***	-***	+*	+***		+†
UUS	-*	-†		-*	+***	+*	+**	+*
# Nominations								
Tx Condition	+**				-***			-†

UUS refers to unsupervised, unstructured socializing. † p < .10 * p < .05 ** p < .01 *** = p < .000. All estimates that were not statistically significant (including marginal significance at p < .10) are listed as blanks.

Table B2. Direction and Significance of Control Variable Effects Predicting Resilience in Multigroup Models

	6th – 8th grade				7th – 9th				8th – 10th				9th – 11th			
	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP
Prior Deviance	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***	-***
Male	-*								-*	-**			-***			
White	+†									+†						
Free Lunch	-**				-*	-**		-*	-*		-†				-†	
Parental Monitoring	+†	+†		+†	+***	+*	+*	+*	+**		.+**		+*	.+**	+*	
Parental Relations	+*															
Impulsivity			-**			-†	-*	-*		-*	-*	-**	-***		-**	-**
UUS		-*	-†											-**		
# Nominations														+†	-**	
Tx Condition	+*	+*														

DP refers to deviant peers. UUS refers to unsupervised, unstructured socializing. † p < .10 * p < .05 ** p < .01 *** = p < .000. All estimates that were not statistically significant (including marginal significance at p < .10) are listed as blanks.

Table B3. Direction and Significance of Control Variable Effects Predicting Change in Deviant Peer Proportion in Multigroup Models

	6th – 8th grade				7th – 9th				8th – 10th				9th – 11th			
	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP	Low DP	Mid DP	High DP	All DP
Prior Deviance	+**	+**			+†	+***	+†		+***	+*	+***	+*	+**	+**		
Male	+***	+***	+*	+*	+**	+**			+*	+†	+**		+*	+†		+*
White			+*		-*	-***										
Free Lunch	+**				+**	+†	+*		+†	+**			+*			
Parental Monitoring				-*	-*		-*								-†	
Parental Relations														-**		
Impulsivity	+†	+*			+*											
UUS	+**		+*	+**					+**	+**				+†	+†	
# Nominations	+***				+†						-*	+†				
Tx Condition	-*	-***	-†	-*									-†	-*		

DP refers to deviant peers. UUS refers to unsupervised, unstructured socializing. † p < .10 * p < .05 ** p < .01 *** = p < .000. All estimates that were not statistically significant (including marginal significance at p < .10) are listed as blanks.

Bibliography

Adamczyk-Robinette, S. L., Fletcher, A. C., & Wright, K. (2002). Understanding the authoritative parenting–early adolescent tobacco use link: The mediating role of peer tobacco use. *Journal of Youth and Adolescence, 31*(4), 311-8.

Agnew, R. (1991). The interactive effects of peer variables on delinquency. *Criminology, 29*(1), 47-72.

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology, 30*(1), 47-88.

Akers, R. L. (1973). *Deviant behavior: A social learning approach.* Wadsworth Publishing Company.

Akers, R. L. (1990). Rational choice, deterrence, and social learning theory in criminology: The path not taken. J. Crim. L. & Criminology, 81, 653.

Akers, R. L. (1998). *Social learning and social structure: A general theory of crime and deviance*. Boston, MA: Northeastern University Press.

Akers, R. L. (1996). Is differential association/social learning cultural deviance theory? *Criminology 34*(2), 229-47.

Akers, R. L., & Krohn, M. D., Lanza-Kaduce, L., & Radosevich, M. (1979). Social learning and deviant behavior: A specific test of a general theory. *American Sociological Review, 44*(4), 636-655.

Albert, D., Chein, J., & Steinberg, L. (2013). The teenage brain: Peer influences on adolescent decision making. *Current Directions in Psychological Science, 22*(2), 114-120.

Aloise-Young, P. A., Graham, J. W., & Hansen, W. B. (1994). Peer influence on smoking initiation during early adolescence: a comparison of group members and group outsiders. *Journal of Applied Psychology, 79*(2), 281.

Anwar, S., & Loughran, T. A. (2011). Testing a Bayesian learning theory of deterrence among serious juvenile offenders. *Criminology, 49*(3), 667-98.

Arneklev, B. J., Grasmick, H. G., & Bursik, R. J. (1999). Evaluating the dimensionality and invariance of" low self-control". Journal of Quantitative Criminology, 15(3), 307-331.

Asparouhov, T. (2005). Sampling weights in latent variable modeling. *Structural Equation Modeling, 12*(3), 411-34.

Asparouhov, T., & Muthén, B. (2010). Weighted least squares estimation with missing data. *Mplus Technical Appendix, 2010*, 1-10.

Baals, D. (2018). Disadvantage and social relations: Short-and long-term effects of stratification in social relations during adolescence (Doctoral dissertation, Pennsylvania State University).

Bandalos, D. L. (2014). Relative performance of categorical diagonally weighted least squares and robust maximum likelihood estimation. *Structural Equation Modeling: a multidisciplinary journal, 21*(1), 102-16.

Bandura, A. (1965). Influence of models' reinforcement contingencies on the acquisition of imitative responses. *Journal of Personality and Social Psychology, 1*(6), 589-95.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*(1), 1-26.

Bandura, A., Ross, D., & Ross, S. A. (1961). Transmission of aggression through imitation of aggressive models. *The Journal of Abnormal and Social Psychology, 63*(3), 575-82.

Barnes, G. M., Hoffman, J. H., Welte, J. W., Farrell, M. P., & Dintcheff, B. A. (2006). Effects of parental monitoring and peer deviance on substance use and delinquency. *Journal of Marriage and Family, 68*(4), 1084-1104.

Baron, J. (2004). Normative models of judgment and decision making. In D. J. Koehler, & N. Harvey (Eds.), *Blackwell Handbook of Judgment and Decision Making* (p. 19–36). Blackwell Publishing Ltd.

Baron, R. A., & Markman, G. D. (2003). Beyond social capital: The role of entrepreneurs' social competence in their financial success. *Journal of Business Venturing, 18*(1), 41-60.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-82.

Barry, C. M., & Wentzel, K. R. (2006). Friend influence on prosocial behavior: The role of motivational factors and friendship characteristics. *Developmental Psychology, 42*(1), 153-63.

Becker, G. S. (1964). Human Capital. *National Bureau of Economic Research, 8*(299), 493-517.

Becker, G. S. (1968). Crime and punishment: An economic approach. In Becker, G. S., Clarke, A., Fielding, N. G., & Witt, R. (Eds.), *The economic dimensions of crime* (p. 13-68). London: Palgrave Macmillan.

Becker, H. (1963). *Outsiders: Studies in the sociology of deviance.* Glencoe, NY: The Free Press.

Beggs, J. J., Haines, V. A., & Hurlbert, J. S. (1996). Revisiting the rural□urban contrast: Personal networks in nonmetropolitan and metropolitan settings. *Rural Sociology, 61*(2), 306-325.

Bentham, J. ([1789] 1948). *An introduction to the principle of morals and legislations.* Oxford, UK: Blackwell.

Bernburg, J. G., & Krohn, M. D. (2003). Labeling, life chances, and adult crime: The direct and indirect effects of official intervention in adolescence on crime in early adulthood. *Criminology, 41*(4), 1287-1318.

Bernburg, J. G., Krohn, M. D., & Rivera, C. J. (2006). Official labeling, criminal embeddedness, and subsequent delinquency: A longitudinal test of labeling theory. *Journal of Research in Crime and Delinquency, 43*(1), 67-88.

Berndt, T. J. (1979). Developmental changes in conformity to peers and parents. *Developmental Psychology, 15*(6), 608-16.

Berndt, T. J. (1989). Obtaining support from friends during childhood and adolescence. In Belle, D. (Ed.), *Children's Social Networks and Social Supports*, (p. 308-331). New York: Wiley.

Bielick, S., & Chapman, C. (2003). *Trends in the use of school choice: 1993 to 1999*. Statistical Analysis Report. Jessup, MD: ED Pubs.

Blakemore, S. J., & Choudhury, S. (2006). Development of the adolescent brain: implications for executive function and social cognition. *Journal of Child Psychology and Psychiatry, 47*(3□4), 296-312.

Boman IV, J. H., & Ward, J. T. (2014). Beyond projection: Specifying the types of peer delinquency misperception at the item and scale levels. *Deviant Behavior, 35*(7), 555-80.

Botvin, G. J., & Griffin, K. W. (2004). Life skills training: Empirical findings and future directions. *Journal of Primary Prevention, 25*(2), 211-32.

Botvin, G. J., Malgady, R. G., Griffin, K. W., Scheier, L. M., & Epstein, J. A. (1998). Alcohol and marijuana use among rural youth: Interaction of social and intrapersonal influences. *Addictive Behaviors, 23*(3), 379-387.

Bourdieu, P. (1980). Le capital social: notes provisoires. *Actes de la Recherche en Sciences Sociales, 31*(1), 2-3.

Bourdieu, P. (1986). The forms of capital. In Richardson, J. G. (Ed.), *Handbook of Theory and Research for the Sociology of Education,* (p 241-58). New York: Greenwood Press.

Boxer, P., Guerra, N. G., Huesmann, L. R., & Morales, J. (2005). Proximal peer-level effects of a small-group selected prevention on aggression in elementary school children: An investigation of the peer contagion hypothesis. Journal of *Abnormal Child Psychology, 33*(3), 325-38.

Brame, R., Bushway, S. D., Paternoster, R., & Turner, M. G. (2014). Demographic patterns of cumulative arrest prevalence by ages 18 and 23. *Crime & Delinquency, 60*(3), 471-486.

Brame, R., Turner, M. G., Paternoster, R., & Bushway, S. D. (2012). Cumulative prevalence of arrest from ages 8 to 23 in a national sample. *Pediatrics, 129*(1), 21-27.

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence, 21*(1), 166-79.

Breckinridge, S.P., & Abbott, E. (1912). *The delinquent child and the home.* New York: Russell Sage Foundation Charities Publication Committee.

Brehm, J., & Rahn, W. (1997). Individual-level evidence for the causes and consequences of social capital. *American Journal of Political Science, 41*(3), 999-1023.

Brittain, C. V. (1963). Adolescent choices and parent-peer cross-pressures. *American Sociological Review, 28*(3), 385-391.

Brown, B. B., Dolcini, M. M., & Leventhal, A. (1997). Transformations in peer relationships at adolescence: Implications for health-related behavior. In J. Schulenberg, J. L. Maggs, & K. Hurrelmann (Eds.), *Health risks and developmental transitions during adolescence* (p. 161–189). Cambridge University Press.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In: Bollen, K.A., Long, J.S. (Eds.) *Testing structural equation models* (p. 111-35). Beverly Hills, CA: Sage.

Burgess, R. L., & Akers, R. L. (1966). A differential association-reinforcement theory of criminal behavior. *Social Problems, 14*(2), 128-147.

Burk, W. J., Van Der Vorst, H., Kerr, M., & Stattin, H. (2012). Alcohol use and friendship dynamics: Selection and socialization in early-, middle-, and late-

adolescent peer networks. *Journal of Studies on Alcohol and Drugs, 73*(1), 89-98.

Burt, C. H., Sweeten, G., & Simons, R. L. (2014). Self□control through emerging adulthood: Instability, multidimensionality, and criminological significance. *Criminology, 52*(3), 450-87.

Byrnes, J. P. (2002). The development of decision-making. *Journal of Adolescent Health, 31*(6), 208-15.

Carson, D. C. (2013). Perceptions of prosocial and delinquent peer behavior and the effect on delinquent attitudes: A longitudinal study. *Journal of Criminal Justice, 41*(3), 151-161.

Cham, H., Reshetnyak, E., Rosenfeld, B., & Breitbart, W. (2017). Full information maximum likelihood estimation for latent variable interactions with incomplete indicators. *Multivariate Behavioral Research, 52*(1), 12-30.

Chein, J., Albert, D., O'Brien, L., Uckert, K., & Steinberg, L. (2011). Peers increase adolescent risk taking by enhancing activity in the brain's reward circuitry. *Developmental Science, 14*(2), F1-F10.

Christiansen, E. J., & Evans, W. P. (2005). Adolescent victimization: Testing models of resiliency by gender. *The Journal of Early Adolescence, 25*(3), 298-316.

Chung, H. L., & Steinberg, L. (2006). Relations between neighborhood factors, parenting behaviors, peer deviance, and delinquency among serious juvenile offenders. *Developmental Psychology, 42*(2), 319.

Claes, M., & Simard, R. (1992). Friendship characteristics of delinquent adolescents. *International Journal of Adolescence and Youth, 3*(3-4), 287-301.

Clarke, R. V., & Cornish, D. B. (1985). Modeling offenders' decisions: A framework for research and policy. *Crime and Justice, 6*, 147-85.

Cohen, J. M. (1977). Sources of peer group homogeneity. *Sociology of Education*, *50*(4), 227-41.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95-S120.

Coleman, J. S. (1994). *Foundations of social theory.* Harvard University Press.

Collins W. A., & L., Steinberg. (2006). Adolescent development in interpersonal context. In: Eisenberg, N., Damon, W., & Lerner, R. (Eds.) *Handbook of child psychology: Social, emotional, and personality development* (p. 1003—67) New York: Wiley.

Condly, S. J. (2006). Resilience in children: A review of literature with implications for education. *Urban Education*, *41*(3), 211-236.

Cooley, C. H. (1902). *Human Nature and the Social Order.* New York: Charles Scribner's Sons.

Cornish, D. B., & Clarke, R. V. (1986). *The reasoning criminal: Rational choice perspectives on offending*. New York: Springer-Verlag.

Cressey, D. R. (1955). Changing criminals: The application of the theory of differential association. *American Journal of Sociology, 61*(2), 116-20.

Demuth, S. (2004). Understanding the delinquency and social relationships of loners. *Youth & Society, 35*(3), 366-92.

DiMaggio, P., & Mohr, J. (1985). Cultural capital, educational attainment, and marital selection. *American Journal of Sociology, 90*(6), 1231-61.

Dishion, T. J., & Loeber, R. (1985). Adolescent marijuana and alcohol use: The role of parents and peers revisited. *The American Journal of Drug and Alcohol Abuse, 11*(1-2), 11-25.

Duncan, G. J., Boisjoly, J., Kremer, M., Levy, D. M., & Eccles, J. (2005). Peer effects in drug use and sex among college students. *Journal of Abnormal Child Psychology, 33*(3), 375-85.

Ellickson, P. L., Bell, R. M., Harrison, E., McGuigan, K. A., Hawes-Dawson, J., & Reinisch, E. J. (2000). Helping adolescents resist drugs. *RAND Research Brief.*

Elliott, D. S., Ageton, S. S., & Canter, R. J. (1979). An integrated theoretical perspective on delinquent behavior. *Journal of Research in Crime and Delinquency, 16*(1), 3-27.

Elliott, D. S., Huizinga, D., & Ageton, S. S. (1985). *Explaining delinquency and drug use.* Sage Publications.

Elliott, D. S., Huizinga, D., & Menard, S. (1989). *Multiple problem youth: Delinquency, drugs and mental health problems.* New York, NY: Springer.

Elliott, D., & Menard, S. (1996). Delinquent friends and delinquent behavior. In J. D. Hawkins (Ed.), *Delinquency and crime: Current theories* (p. 28–67). Cambridge University.

Ellis, B. J., Bianchi, J., Griskevicius, V., & Frankenhuis, W. E. (2017). Beyond risk and protective factors: An adaptation-based approach to resilience. *Perspectives on Psychological Science, 12*(4), 561-587.

Ellis, B. J., Essex, M. J., & Boyce, W. T. (2005). Biological sensitivity to context: II. Empirical explorations of an evolutionary–developmental theory. *Development and Psychopathology, 17*(2), 303-328.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272-99.

Farrell, A. D., Meyer, A. L., Sullivan, T. N., & Kung, E. M. (2003). Evaluation of the Responding in Peaceful and Positive Ways (RIPP) seventh grade violence prevention curriculum. *Journal of Child and Family Studies, 12*(1), 101-120.

Farrington, D. P. (1986). Age and crime. *Crime and Justice, 7*, 189-250.

Farrington, D. P. (1992). Explaining the beginning, progress, and ending of antisocial behavior from birth to adulthood. In McCord, J. (Ed.) *Facts, frameworks, and forecasts* (p. 253-86). Transaction Publishers.

Felmlee, D. H., McMillan, C., Rodis, P. I., & Osgood, D. W. (2018). The evolution of youth friendship networks from 6th to 12th grade: School transitions, popularity and centrality. In *Social networks and the life course* (p. 161-184). Cham, Switzerland: Springer.

Fenneman, J., & Frankenhuis, W. E. (2020). Is impulsive behavior adaptive in harsh and unpredictable environments? A formal model. *Evolution and Human Behavior, 41*(4), 261-273.

Fenzel, L. M. (1989). Role strain in early adolescence: A model for investigating school transition stress. *The Journal of Early Adolescence, 9*(1-2), 13-33.

Fergus, S., & Zimmerman, M. A. (2005). Adolescent resilience: A framework for understanding healthy development in the face of risk. *Annual Review of Public Health, 26*, 399-419.

Fergusson, D. M., Vitaro, F., Wanner, B., & Brendgen, M. (2007). Protective and compensatory factors mitigating the influence of deviant friends on delinquent behaviours during early adolescence. *Journal of Adolescence, 30*(1), 33-50.

Frankenhuis, W. E., Young, E. S., & Ellis, B. J. (2020). The hidden talents approach: Theoretical and methodological challenges. *Trends in Cognitive Sciences, 24*(7), 569-581.

Furstenberg F. F., Jr., & Hughes, M. E. (1995). Social capital and successful development among at-risk youth. *Journal of Marriage and the Family, 57*(3) 580-592.

Gallupe, O., McLevey, J., & Brown, S. (2019). Selection and influence: A meta-analysis of the association between peer and personal offending. *Journal of Quantitative Criminology, 35*(2), 313-335.

Gardner, T. W., Dishion, T. J., & Connell, A. M. (2008). Adolescent self-regulation as resilience: Resistance to antisocial behavior within the deviant peer context. *Journal of Abnormal Child Psychology, 36*(2), 273-84.

Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study. *Developmental Psychology, 41*(4), 625-35.

Garmezy, N. (1973). Competence and adaptation in adult schizophrenic patients and children at risk. *Schizophrenia: The First Ten Dean Award Lectures*, 163-204.

Garmezy, N. (1985). Stress-resistant children: The search for protective factors. *Recent Research in Developmental Psychopathology, 4*, 213-33.

Garmezy, N. (1987). Stress, competence, and development: Continuities in the study of schizophrenic adults, children vulnerable to psychopathology, and the search for stress□resistant children. *American Journal of Orthopsychiatry, 57*(2), 159-174.

Garmezy, N., Masten, A. S., & Tellegen, A. (1984). The study of stress and competence in children: A building block for developmental psychopathology. *Child Development, 55*(1), 97-111.

Garrido, E. F., & Taussig, H. N. (2013). Do parenting practices and prosocial peers moderate the association between intimate partner violence exposure and teen dating violence? *Psychology of Violence, 3*(4), 354-66.

Gau, J. M. (2010). Basic principles and practices of structural equation modeling in criminal justice and criminology research. *Journal of Criminal Justice Education, 21*(2), 136-51.

Gibbs, J. P. (1968). Crime, punishment, and deterrence. The Southwestern Social Science Quarterly, 515-530.

Giordano, P. C. (1989). Confronting control theory's negative cases. In Messner, S. F., Krohn, M. D., & Liska, A. E. (Eds.) *Theoretical integration in the study of crime and deviance: Problems and prospects*. Albany, NY: State University of New York Press.

Giordano, P. C., Cernkovich, S. A., & Lowery, A. R. (2004). A Long-Term Follow-Up of Serious Adolescent Female Offenders. In M. Putallaz & K. L. Bierman

(Eds.), *Aggression, antisocial behavior, and violence among girls: A developmental perspective* (p. 186–202). Guilford Publications.

Giordano, P. C., Cernkovich, S. A., & Rudolph, J. L. (2002). Gender, crime, and desistance: Toward a theory of cognitive transformation. *American Journal of Sociology 107*(4), 990-1064.

Glueck, S, & Glueck, E. 1950. *Unraveling juvenile delinquency.* New York: Commonwealth Fund.

Goodnight, J. A., Bates, J. E., Newman, J. P., Dodge, K. A., & Pettit, G. S. (2006). The interactive influences of friend deviance and reward dominance on the development of externalizing behavior during middle adolescence. *Journal of Abnormal Child Psychology, 34*(5), 573-83.

Gottfredson, M. R., & Hirschi, T. (1990). *A general theory of crime.* Stanford University Press.

Gottfredson, M., & Hirschi, T. (2019). *Modern control theory and the limits of criminal justice.* Oxford University Press.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology, 91*(3), 481-510.

Grasmick, H. G., Tittle, C. R., Bursik Jr, R. J., & Arneklev, B. J. (1993). Testing the core empirical implications of Gottfredson and Hirschi's general theory of crime. Journal of research in crime and delinquency, 30(1), 5-29.

Greenberg, M. T., Kusche, C. A., Cook, E. T., & Quamma, J. P. (1995). Promoting emotional competence in school-aged children: The effects of the PATHS curriculum. *Development and Psychopathology, 7*(1), 117-136.

Grosbras, M. H., Jansen, M., Leonard, G., McIntosh, A., Osswald, K., Poulsen, C., Steinberg, L., Toro, R., & Paus, T. (2007). Neural mechanisms of resistance to peer influence in early adolescence. *Journal of Neuroscience, 27*(30), 8040-5.

Hagan, J., MacMillan, R., & Wheaton, B. (1996). New kid in town: Social capital and the life course effects of family migration on children. *American Sociological Review, 61*(3), 368-85.

Hagan, J., & McCarthy, B. (1997). *Mean streets: Youth crime and homelessness.* Cambridge University Press.

Hancock, G. R., & Mueller, R. O. (2013). *Structural equation modeling: A second course*. 2nd Ed. Information Age Publishing.

Hancock, G. R., & Wasko, J. A. (2010, May). Preliminary assessments of normality are useless in deciding whether or not to use rescaled model test statistics. Paper presented at the Annual Meeting of the American Educational Research Association, Denver, CO.

Hansen, W. B., & Dusenbury, L. (2004). All Stars Plus: A competence and motivation enhancement approach to prevention. *Health Education, 4*(6), 371-81.

Harwell, M., & LeBeau, B. (2010). Student eligibility for a free lunch as an SES measure in education research. *Educational Researcher, 39*(2), 120-31.

Hauser, R. M., & Goldberger, A. S. (1971). The treatment of unobservable variables in path analysis. *Sociological Methodology, 3*, 81-117.

Hayes, A. F., & Preacher, K. J. (2013). Conditional process modeling: Using structural equation modeling to examine contingent causal processes. In G. R.

Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (p. 219–66). Information Age Publishing.

Haynie, D. L. (2002). Friendship networks and delinquency: The relative nature of peer delinquency. *Journal of Quantitative Criminology, 18*(2), 99-134.

Haynie, D. L., & Osgood, D. W. (2005). Reconsidering peers and delinquency: How do peers matter? *Social Forces, 84*(2), 1109-30.

Heller, S. B., Shah, A. K., Guryan, J., Ludwig, J., Mullainathan, S., & Pollack, H.A. (2017). Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago. *The Quarterly Journal of Economics, 132*(1): 1-54.

Henderson, N., & Milstein, M. M. (2003). *Resiliency in schools: Making it happen for students and educators.* Corwin Press.

Hindelang, M. J., Hirschi, T., & Weis, J. G. (1981). *Measuring delinquency.* Beverly Hills: Sage.

Huizinga, D., & Elliott, D. S. (1986). Reassessing the reliability and validity of self-report delinquent measures. Journal of Quantitative Criminology 2(4): 293-327.

Hirschi, T. (1969). *Causes of Delinquency.* Berkeley, CA: University of California.

Hirschi, T. (1996). Theory without ideas: Reply to Akers. *Criminology, 34*(2), 249-56.

Hirschi, T. (2004). Self-control and crime. In Baumeister, R. F., & Vohs, K. D. (Eds.), *Handbook of self-regulation: Research, theory, and applications* (p. 537-52). The Guilford Press.

Hirschi, T., & Gottfredson, M. R. (1994). *The generality of deviance.* NJ: Transaction Publishers.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Jacobsen, W. C. (2020). School punishment and interpersonal exclusion: Rejection, withdrawal, and separation from friends. *Criminology, 58*(1), 35-69.

Jacobsen, W. C., Ragan, D. T., Yang, M., Nadel, E. L., & Feinberg. M. E. (2018). Juvenile Arrest Stigma and the Mechanisms of Interpersonal Exclusion. Paper presented at the Annual Meeting of the American Society of Criminology, Philadelphia, PA.

James, L. R., & Brett, J. M. (1984). Mediators, moderators, and tests for mediation. *Journal of Applied Psychology, 69*(2), 307-21.

Jeffrey, C. R. (1965). Criminal behavior and learning theory. *Journal of Criminal Law, Criminology, and Police Science 56*, 294-300.

Jöreskog, K. G. (1973). Analysis of covariance structures. In *Multivariate analysis–III* (p. 263-85). Academic Press.

Judd, C. M., & Kenny, D. A. (1981). Process analysis: Estimating mediation in treatment evaluations. *Evaluation Review, 5*(5), 602-19.

Jussim, L., & Osgood, D. W. (1989). Influence and similarity among friends: An integrative model applied to incarcerated adolescents. *Social Psychology Quarterly, 52*(2), 98-112.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review, 93*(5), 1449-75.

Kahneman, D. (2011). *Thinking, fast and slow.* Macmillan.

Kandel, D. B. (1978). Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology, 84*(2), 427-36.

Kandel, D. B. (1996). The parental and peer contexts of adolescent deviance: An algebra of interpersonal influences. *Journal of Drug Issues, 26*(2), 289-315.

Kang-Brown, J., & Subramanian, R. (2017). *Out of sight: The growth of jails in rural America.* New York, NY: Vera Institute of Justice.

Keesling, J.W. (1972). Maximum likelihood approach to causal analysis. (Doctoral dissertation, University of Chicago).

Kline, R. B. (2011). Convergence of structural equation modeling and multilevel modeling. In Williams, M., & Vogt, W. P. (Eds.) The SAGE handbook of innovation in social research methods. Sage.

Kolar, K. (2011). Resilience: Revisiting the concept and its utility for social research. *International Journal of Mental Health and Addiction, 9*(4), 421-33.

Kornhauser, R. R. (1978). *Social sources of delinquency: An appraisal of analytic models.* Chicago: University of Chicago Press.

Kreager, D. A. (2004). Strangers in the halls: Isolation and delinquency in school networks. *Social Forces, 83*(1), 351-390.

Kreager, D. A., Rulison, K., & Moody, J. (2011). Delinquency and the structure of adolescent peer groups. *Criminology, 49*(1), 95-127.

Laub, J. H., & Sampson, R. J. (1993). Turning points in the life course: Why change matters to the study of crime. Criminology, 31(3), 301-325.

Laub, J. H., & Sampson, R. J. (2001). Understanding desistance from crime. *Crime and Justice, 28*, 1-69.

Lemert, E. M. (1951). *Social pathology; A systematic approach to the theory of sociopathic behavior.* McGraw-Hill.

Leung, R. K., Toumbourou, J. W., & Hemphill, S. A. (2014). The effect of peer influence and selection processes on adolescent alcohol use: a systematic review of longitudinal studies. *Health Psychology Review, 8*(4), 426-57.

Li, C. H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods, 48*(3), 936-49.

Liebenberg, L., & Ungar, M. (2009). Introduction: The challenges in researching resilience. In Ungar, M., & Liebenberg, L. (Eds). *Researching resilience* (p. 3-25). University of Toronto Press.

Lin, N. (2002). *Social capital: A theory of social structure and action*. Cambridge University Press.

Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*(404), 1198-1202.

Lochner, L. (2007). Individual perceptions of the criminal justice system. *American Economic Review, 97*(1), 444-60.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes, 65*(3), 272-92.

Loughran, T. A., Nguyen, H., Piquero, A. R., & Fagan, J. (2013). The returns to criminal capital. *American Sociological Review, 78*(6), 925-48.

Loughran, T. A., Paternoster, R., Piquero, A. R., & Pogarsky, G. (2011). On ambiguity in perceptions of risk: Implications for criminal decision making and deterrence. *Criminology, 49*(4), 1029-61.

Luthar, S. S. (1991). Vulnerability and resilience: A study of high□risk adolescents. *Child Development, 62*(3), 600-16.

Luthar, S. S. (2006). Resilience in development: A synthesis of research across five decades. In D. Cicchetti & D. J. Cohen (Eds.), *Developmental psychopathology: Risk, disorder, and adaptation* (p. 739–95). John Wiley & Sons Inc.

Luthar, S. S., Doernberger, C. H., & Zigler, E. (1993). Resilience is not a unidimensional construct: Insights from a prospective study of inner-city adolescents. *Development and Psychopathology, 5*(4), 703-17.

Mamayek, C., Paternoster, R., & Loughran, T. A. (2017). Self-control as self-regulation: A return to control theory. *Deviant Behavior, 38*(8), 895-916.

Mann, L., Harmoni, R., & Power, C. (1989). Adolescent decision-making: The development of competence. *Journal of Adolescence, 12*(3), 265-78.

Marsden, P. V., & Srivastava, S. B. (2012). Trends in informal social participation, 1974-2008. In Marsden, P. V. (Ed), *Social trends in American life: Findings*

from the General Social Survey since 1972, (p. 240-263). Princeton University Press.

Maruna, Shadd. 2001. *Making good: How ex-convicts reform and rebuild their lives.* Washington, DC: American Psychological Association.

Masten, A. S. (2001). Ordinary magic: Resilience processes in development. *American Psychologist*, *56*(3), 227-38.

Masten, A. S. (2011). Resilience in children threatened by extreme adversity: Frameworks for research, practice, and translational synergy. *Development and Psychopathology, 23*(2), 493-506.

Masten, A. S., & Coatsworth, J. D. (1995). Competence, resilience, and psychopathology. In D. Cicchetti & D. J. Cohen (Eds.), *Developmental psychopathology: Risk, disorder, and adaptation* (p. 715–52). John Wiley & Sons.

Masten, A. S., & Obradović, J. (2006). Competence and resilience in development. *Annals of the New York Academy of Sciences, 1094*(1), 13-27.

Masten, A. S., & Powell, L. (2003). A Resilience Framework for Research, Policy. In Cicchetti, D. (Ed.) *Resilience and vulnerability: Adaptation in the context of childhood adversities* (p. 364-91). Cambridge University Press.

Matsueda, R. L. (1982). Testing control theory and differential association: A causal modeling approach. American sociological review, 489-504.

Matsueda, R. L. (1988). The current state of differential association theory. *Crime & Delinquency, 34*(3), 277-306.

Matsueda, R. L. (1992). Reflected appraisals, parental labeling, and delinquency: Specifying a symbolic interactionist theory. *American Journal of Sociology, 97*(6), 1577-1611.

Matsueda, R. L., & Anderson, K. (1998). The dynamics of delinquent peers and delinquent behavior. *Criminology, 36*(2), 269-308.

Matsueda, R. L., Kreager, D. A., & Huizinga, D. (2006). Deterring delinquents: A rational choice model of theft and violence. *American Sociological Review, 71*(1), 95-122.

Matza, D. (1964). *Delinquency and drift.* New York: John Wiley & Sons, Inc.

McCarthy, B., & Hagan, J. (1995). Getting into street crime: The structure and process of criminal embeddedness. *Social Science Research, 24*(1), 63-95.

McCarthy, B. (2002). New economics of sociological criminology. *Annual Review of Sociology*, *28*(1), 417-42.

McGivern, M. S. (2010). The impact of cognitive coping on the strain-delinquency relationship: A test of general strain theory (Master of Arts thesis, University of Iowa).

McGloin, J. M. (2009). Delinquency balance: Revisiting peer influence. *Criminology, 47*(2), 439-77.

McGloin, J. M., Sullivan, C. J., & Thomas, K. J. (2014). Peer influence and context: the interdependence of friendship groups, schoolmates and network density in predicting substance use. *Journal of Youth and Adolescence, 43*(9), 1436-52.

McGloin, J. M., & Thomas, K. J. (2016). Considering the elements that inform perceived peer deviance. *Journal of Research in Crime and Delinquency, 53*(5), 597-627.

McGloin, J. M., & Thomas, K. J. (2019). Peer influence and delinquency. *Annual Review of Criminology, 2:* 241-264.

McGloin, J. M., & Widom, C. S. (2001). Resilience among abused and neglected children grown up. *Development and Psychopathology, 13*(4), 1021-38.

Mead, G. H. (1934). *Mind, self and society.* Chicago: University of Chicago Press.

Meldrum, R. C., Miller, H. V., & Flexon, J. L. (2013). Susceptibility to peer influence, self□control, and delinquency. *Sociological Inquiry, 83*(1), 106-29.

Mercken, L., Steglich, C., Sinclair, P., Holliday, J., & Moore, L. (2012). A longitudinal social network analysis of peer influence, peer selection, and smoking behavior among adolescents in British schools. *Health Psychology, 31*(4), 450-9.

Meyers, L. S., Gamst, G. C., & Guarino, A. J. (2013). *Performing data analysis using IBM SPSS.* John Wiley & Sons.

Moffitt, T. E. (1993). Adolescence-limited and life-course-persistent antisocial behavior: a developmental taxonomy. *Psychological Review, 100*(4) 674-701.

Monahan, K. C., Steinberg, L., & Cauffman, E. (2009). Affiliation with antisocial peers, susceptibility to peer influence, and antisocial behavior during the transition to adulthood. *Developmental Psychology*, *45*(6), 1520-30.

Mortimer, J. T., & Staff, J. (2004). Early work as a source of developmental discontinuity during the transition to adulthood. *Development and Psychopathology, 16*(4), 1047-1070.

Mrug, S., & Windle, M. (2009). Moderators of negative peer influence on early adolescent externalizing behaviors: Individual behavior, parenting, and school connectedness. *The Journal of Early Adolescence, 29*(4), 518-540.

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin, 105*(3), 430-45.

Musu-Gillette, L., de Brey, C., McFarland, J., Hussar, W., Sonnenberg, W., & Wilkinson-Flicker, S. (2017). *Status and trends in the education of racial and ethnic groups 2017*. U.S. Department of Education.

Muthén, L.K., & Muthén, B.O. (1998-2010). Mplus User's Guide. Sixth Edition. Los Angeles, CA: Muthén & Muthén.

Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2015). Estimator choices with categorical outcomes. Mplus and Mplus.

Na, C., & Gottfredson, D. C. (2013). Police officers in schools: Effects on school crime and the processing of offending behaviors. *Justice Quarterly, 30*(4), 619-650.

Nagin, D. S. (2007). Moving choice to center stage in criminological research and theory. *Criminology, 45*(2)*,* 259-72.

Nagin, D. S., & Paternoster, R. (1993). Enduring individual differences and rational choice theories of crime. *Law and Society Review 27*(3), 467-96.

Nagin, D. S., & Paternoster, R. (1994). Personal capital and social control: The deterrence implications of a theory of individual differences in criminal offending. *Criminology, 32*(4), 581-606.

Nagin, D. S., & Pogarsky, G. (2001). Integrating celerity, impulsivity, and extralegal sanction threats into a model of general deterrence: Theory and evidence. *Criminology, 39*(4), 865-892.

Nagin, D. S., & Pogarsky, G. (2004). Time and punishment: Delayed consequences and criminal behavior. *Journal of Quantitative Criminology, 20*(4), 295-317.

Nunnally, J. (1967). *Psychometric Theory.* New York: McGraw Hill.

Nye, C. D., & Drasgow, F. (2011). Assessing goodness of fit: Simple rules of thumb simply do not work. *Organizational Research Methods, 14*(3), 548-570.

O'Brien, L., Albert, D., Chein, J., & Steinberg, L. (2011). Adolescents prefer more immediate rewards when in the presence of their peers. *Journal of Research on Adolescence, 21*(4), 747-753.

Osgood, D. W., Baals, D.A., & Ramirez, N. G. Does free and reduced-price lunch measure up? A methodological examination of how to measure an adolescent's socioeconomic background. Unpublished.

Osgood, D. W., Feinberg, M. E., Gest, S. D., Moody, J., Ragan, D. T., Spoth, R., Greenberg, M., & Redmond, C. (2013a). Effects of PROSPER on the influence potential of prosocial versus antisocial youth in adolescent friendship networks. *Journal of Adolescent Health, 53*(2), 174-179.

Osgood, D. W., Feinberg, M. E., & Ragan, D. T. (2015). Social networks and the diffusion of adolescent problem behavior: Reliable estimates of selection and influence from sixth through ninth grades. *Prevention Science, 16*(6), 832-43.

Osgood, D. W., & McMillan, C. (2019). Influenced by how any friends? A pervasive methodological artefact and how to solve it. Paper presented at the Annual Meeting of the American Society of Criminology, San Francisco, CA.

Osgood, D. W., Ragan, D. T., Wallace, L., Gest, S. D., Feinberg, M. E., & Moody, J. (2013b). Peers and the emergence of alcohol use: Influence and selection processes in adolescent friendship networks. *Journal of Research on Adolescence, 23*(3), 500-512.

Osgood, D. W., Wilson, J. K., O'Malley, P. M., Bachman, J. G., & Johnston, L. D. (1996). Routine activities and individual deviant behavior. *American Sociological Review, 61*(4), 635-55.

Paternoster, R., & Bushway, S. (2009). Desistance and the" feared self": Toward an identity theory of criminal desistance. *The Journal of Criminal Law and Criminology, 99*(4), 1103-1156.

Paternoster, R., McGloin, J. M., Nguyen, H., & Thomas, K. J. (2013). The causal impact of exposure to deviant peers: An experimental investigation. *Journal of Research in Crime and Delinquency, 50*(4), 476-503.

Paternoster, R., & Pogarsky, G. (2009). Rational choice, agency and thoughtfully reflective decision making: The short and long-term consequences of making good choices. *Journal of Quantitative Criminology, 25*(2), 103-27.

Paternoster, R., Pogarsky, G., & Zimmerman, G. (2011). Thoughtfully reflective decision making and the accumulation of capital: Bringing choice back in. *Journal of Quantitative Criminology, 27*(1), 1-26.

Paternoster, R., Saltzman, L. E., Waldo, G. P., & Chiricos, T. G. (1983). Perceived risk and social control: Do sanctions really deter? *Law and Society Review, 17*(3), 457-79.

Payne, D. C., & Cornwell, B. (2007). Reconsidering peer influences on delinquency: Do less proximate contacts matter? *Journal of Quantitative Criminology, 23*(2), 127-49.

Piquero, N. L., Gover, A. R., MacDonald, J. M., & Piquero, A. R. (2005). The influence of delinquent peers on delinquency: Does gender matter? *Youth & Society, 36*(3), 251-275.

Pratt, T. C., & Cullen, F. T. (2000). The empirical status of Gottfredson and Hirschi's general theory of crime: A meta□analysis. *Criminology, 38*(3), 931-64.

Pratt, T. C., Cullen, F. T., Sellers, C. S., Winfree, L. T., Jr., L., Madensen, T. D., Daigle, L. E., Daigle, L. E., Fearn, N. E., & Gau, J. M. (2010). The empirical status of social learning theory: A meta□analysis. *Justice Quarterly, 27*(6): 765-802.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research, 42*(1), 185-227.

Prinstein, M. J., Boergers, J., & Spirito, A. (2001). Adolescents' and their friends' health-risk behavior: Factors that alter or add to peer influence. *Journal of Pediatric Psychology, 26*(5), 287-98.

Putnam, R. D. (1995). Tuning in, tuning out: The strange disappearance of social capital in America. *PS: Political science & politics, 28*(4), 664-83.

Putnam, R. D. (2000). *Bowling alone: The collapse and revival of American community.* Simon and Schuster.

Putnam, R. (2001). Social capital: Measurement and consequences. *Canadian Journal of Policy Research, 2*(1), 41-51.

Ragan, D. T. (2016). Peer beliefs and smoking in adolescence: a longitudinal social network analysis. The American Journal of Drug and Alcohol Abuse, 42(2), 222-30.

Ragan, D. T. (2020). Similarity between deviant peers: Developmental trends in influence and selection. *Criminology.*

Ragan, D. T., Osgood, D. W., Ramirez, N. G., Moody, J., & Gest, S. D. (2019). A comparison of peer influence estimates from SIENA stochastic actor–based models and from conventional regression approaches. *Sociological Methods & Research*, 1-39.

Ramsay, J.R., Rostain, A.L. (2008). *Cognitive behavioral therapy for adult ADHD: an integrative psychosocial and medical approach.* New York: Routledge.

Reckless, W. C., Dinitz, S., & Murray, E. (1957). The “good” boy in a high delinquency area. *Journal of Criminal Law, Criminology, and Police Science, 48,* 18-25.

Rescher, N. (2003). *Sensible decisions: issues of rational decision in personal choice and public policy.* Rowman & Littlefield.

Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods, 17*(3), 354-73.

Rivers III, L., Gibbs, C., & Paternoster, R. (2017). Integrating criminological and decision research theory: implications for understanding and addressing crime in marginalized communities. *Deviant Behavior, 38*(1), 74-93.

Robins, L. N. (1978). Sturdy childhood predictors of adult antisocial behaviour: Replications from longitudinal studies. *Psychological Medicine, 8*(4), 611-22.

Rubin, D. B. (1976). Inference and missing data. *Biometrika, 63*(3), 581-92.

Rutter, M. (1985). Resilience in the face of adversity: Protective factors and resistance to psychiatric disorder. *The British Journal of Psychiatry, 147*(6), 598-611.

Rutter, M. (1987). Psychosocial resilience and protective mechanisms. *American Journal of Orthopsychiatry, 57*(3), 316-31.

Rutter, M. (1990). Psychosocial resilience and protective mechanisms. In Rolf, J., Masten, AS, Cicchetti, D. Nuechterlein, KH and Weintraub, S. (Eds.) *Risk and Protective factors in the development of psychopathology* (p. 316-31). New York: Cambridge University Press.

Rutter, M. (1999). Resilience concepts and findings: Implications for family therapy. *Journal of Family Therapy, 21*(2), 119-144.

Rutter, M. (2000). Resilience reconsidered: Conceptual considerations, empirical findings, and policy implications. In J. P. Shonkoff & S. J. Meisels (Eds.), *Handbook of early childhood intervention* (p. 651–82). Cambridge University Press.

Rutter, M. (2006). Implications of resilience concepts for scientific understanding. *Annals of the New York Academy of Sciences, 1094*(1), 1-12.

Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *The Quarterly Journal of Economics, 116*(2), 681-704.

Saltzman, L., Paternoster, R., Waldo, G. P., & Chiricos, T. G. (1982). Deterrent and experiential effects: The problem of causal order in perceptual deterrence research. *Journal of Research in Crime and Delinquency, 19*(2), 172-89.

Sameroff, A. J. (2000). Developmental systems and psychopathology. *Development and Psychopathology, 12*(3), 297–312.

Sameroff, A., Gutman, L. M., & Peck, S. C. (2003). Adaptation among youth facing multiple risks: Prospective research findings. In Cicchetti, D. (Ed.) *Resilience and vulnerability: Adaptation in the context of childhood adversities* (p. 364-91). Cambridge University Press.

Sampson, R. J., & Laub, J. H. (2003). Life□course desisters? Trajectories of crime among delinquent boys followed to age 70. *Criminology, 41*(3), 555-92.

Sampson, R. J., Morenoff, J. D., & Earls, F. (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review, 64*(5), 633-60.

Sampson, R. J., & Raudenbush, S. W. (1999). Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology, 105*(3), 603-51.

Seligman, M. E. P., & Csikszentmihalyi, M. (2000). Positive psychology: An introduction. *American Psychologist, 55*(1), 5-14.

Sellin, T. (1938). Culture conflict and crime. *American Journal of Sociology, 44*, (1), 97-103.

Shaw, C. R. (1930). *The jack-roller: A delinquent boy's own story*. University of Chicago Press.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. University of Chicago Press.

Sherman, J. (2006). Coping with rural poverty: Economic survival and moral capital in rural america. *Social Forces 85*(2):891-913.

Short, J. F., Jr. (1957). Differential association and delinquency. *Social Problems 4*(3): 233–239.

Silva, B. C., Bosancianu, C. M., & Littvay, L. (2019). *Multilevel structural equation modeling* (Vol. 179). Sage Publications.

Simon. H. A. (1957). *Models of Man*. New York: John Wiley and Sons.

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417-53.

Skinner, B. F. (1938). *The behavior of organisms: An experimental analysis.* New York: Appleton-Century.

Smith, C. (2003). Religious participation and network closure among American adolescents. *Journal for the Scientific Study of Religion, 42*, 259–267.

Smith, C., Lizotte, A. J., Thornberry, T. P., & Krohn, M. D. (1995). Resilient youth: Identifying factors that prevent high-risk youth from engaging in delinquency and drug use. *Current Perspectives on Aging and the Life Course, 4*, 217-47.

Smith, C. A., Park, A., Ireland, T. O., Elwyn, L., & Thornberry, T. P. (2013). Long-term outcomes of young adults exposed to maltreatment: the role of educational experiences in promoting resilience to crime and violence in early adulthood. *Journal of Interpersonal Violence, 28*(1), 121-56.

Smith, M. H., Beaulieu, L. J., & Seraphine, A. (1995). Social capital, place of residence, and college attendance. *Rural Sociology, 60*(3), 363-380.

Snijders, T. A. B. (2001). The statistical evaluation of social network dynamics. *Sociological Methodology, 31*, 361–95.

Snijders, T. A. B. (2005). Models for longitudinal network data. In P. J. Carrington, J. Scott, & S. Wasserman (Eds.), *Models and methods in social network analysis* (p. 215–247). New York, NY: Cambridge University Press.

South, S. J., & Haynie, D. L. (2004). Friendship networks of mobile adolescents. *Social Forces, 83*(1), 315-350.

Spoth, R., Redmond, C., Shin, C., Greenberg, M., Clair, S., & Feinberg, M. (2007). Substance-use outcomes at 18 months past baseline: The PROSPER community-university partnership trial. *American Journal of Preventive Medicine, 32*(5), 395–402.

Stafford, M. C., & Warr, M. (1993). A reconceptualization of general and specific deterrence. *Journal of Research in Crime and Delinquency, 30*(2), 123-35.

Stapleton, L. M., Yang, J. S., & Hancock, G. R. (2016). Construct meaning in multilevel settings. Journal of Educational and Behavioral Statistics, 41(5), 481-520.

StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Steglich, C., Snijders, T. A. B., & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology, 40,* 329–393.

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research, 25*(2), 173-80.

Steinberg, L., & Cauffman, E. (1996). Maturity of judgment in adolescence: Psychosocial factors in adolescent decision making. *Law and Human Behavior, 20*(3), 249-72.

Steinberg, L., Albert, D., Cauffman, E., Banich, M., Graham, S., & Woolard, J. (2008). Age differences in sensation seeking and impulsivity as indexed by behavior and self-report: evidence for a dual systems model. *Developmental Psychology, 44*(6): 1764-78.

Steinberg, L., & Monahan, K. C. (2007). Age differences in resistance to peer influence. Developmental psychology, 43(6), 1531-43.

Steinberg, L., & Silverberg, S. B. (1986). The vicissitudes of autonomy in early adolescence. *Child Development, 57*(4), 841-851.

Stride C.B., Gardner S., Catley. N. & Thomas, F. (2015) Mplus code for mediation, moderation, and moderated mediation models. http://www.offbeat.group.shef.ac.uk/FIO/mplusmedmod.htm

Sturge-Apple, M. L., Suor, J. H., Davies, P. T., Cicchetti, D., Skibo, M. A., & Rogosch, F. A. (2016). Vagal tone and children's delay of gratification: Differential sensitivity in resource-poor and resource-rich environments. *Psychological Science, 27*(6), 885-893.

Suh, Y. (2015). The performance of maximum likelihood and weighted least square mean and variance adjusted estimators in testing differential item functioning with nonnormal trait distributions. *Structural Equation Modeling: A Multidisciplinary Journal, 22*(4), 568-80.

Sullivan, C. J. (2011). The utility of the deviant case in the development of criminological theory. Criminology, 49(3), 905-920.

Sutherland, E H. (1924). *Criminology*. Philadelphia: J. B. Lippincott Company.

Sutherland, E. H. (1937). *The professional thief.* University of Chicago Press.

Sutherland, E. H. (1947). *Principles of Criminology.* Philadelphia: J. B. Lippincott Company.

Sutherland, E. H., & Cressey, D. R. (1960). *Principles of criminology*. Chicago: J. B. Lippincott Company.

Sutherland, E. H., Cressey, D. R., & Luckenbill, D. F. (1992). *Principles of criminology.* Dix Hills, NY: General Hall.

Sweeten, G. (2012). Scaling criminal offending. *Journal of Quantitative Criminology, 28*(3), 533-57.

Sykes, G. M., & Matza, D. (1957). Techniques of neutralization: A theory of delinquency. *American Sociological Review, 22*: 664-670.

Thaler, R. H. (2015). *Misbehaving: The making of behavioral economics.* New York: WW Norton.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness.* Penguin Books.

Thomas, K. J., & Marie McGloin, J. (2013). A dual□systems approach for understanding differential susceptibility to processes of peer influence. *Criminology, 51*(2), 435-74.

Thomas, K. J., McGloin, J. M., & Sullivan, C. J. (2019). Quantifying the likelihood of false positives: Using sensitivity analysis to bound statistical inference. *Journal of Quantitative Criminology, 35*(4), 631-662.

Thornberry, T. P. (1987). Toward an interactional theory of delinquency. *Criminology, 25*(4), 863-92.

Thornberry, T. P., & Krohn, M. D. (2000). The self-report method for measuring delinquency and crime. In Duffee, D. (Ed.) *Measurement and analysis of crime and justice: Criminal justice* (Vol 4, p. 33-83). U.S. Department of Justice Office of Justice Programs.

Thornberry, T. P., & Krohn, M. D. (2011). The self-report method and the development of criminological theory. In MacDonald, J. (Ed.). *Measuring crime and criminality: Advances in criminological theory* (Vol. 1, p. 1-19). Transaction Publishers.

Thornberry, T. P., Lizotte, A. J., Krohn, M. D., Farnworth, M., & Jang, S. J. (1994). Delinquent peers, beliefs, and delinquent behavior: A longitudinal test of interactional theory. *Criminology, 32*(1), 47-83.

Tiet, Q. Q., Huizinga, D., & Byrnes, H. F. (2010). Predictors of resilience among inner city youths. Journal of Child and Family Studies, 19(3), 360-378.

Tittle, C. R. (1969). Crime rates and legal sanctions. *Social Problems, 16*(4), 409-23.

Thorndike, E. L. (1898). Animal intelligence: An experimental study of the associative processes of animals. *Psychological Review Monograph Supplement, 2*, 1–107.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-31.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*(4481), 453-8.

Ungar, M. (Ed.). (2005). *Handbook for working with children and youth: Pathways to resilience across cultures and contexts.* Sage Publications.

Urberg, K. A., Değirmencioğlu, S. M., & Pilgrim, C. (1997). Close friend and group influence on adolescent cigarette smoking and alcohol use. *Developmental Psychology, 33*(5), 834.

Urberg, K. A., Luo, Q., Pilgrim, C., & Degirmencioglu, S. M. (2003). A two-stage model of peer influence in adolescent substance use: Individual and relationship-specific differences in susceptibility to influence. *Addictive Behaviors, 28*(7), 1243-1256.

Van Gelder, J. L. (2013). Beyond rational choice: The hot/cool perspective of criminal decision making. *Psychology, Crime & Law*, *19*(9), 745-63.

Van Gelder, J. L., Averdijk, M., Ribeaud, D., & Eisner, M. (2018). Punitive parenting and delinquency: The mediating role of short-term mindsets. *The British Journal of Criminology, 58*(3), 644-666.

Veenstra, R., & Dijkstra, J. K. (2011). Transformations in adolescent peer networks. In B. Laursen, & W. A. Collins (Eds.), *Relationship pathways: From adolescence to young adulthood* (pp. 135–154). New York: Sage.

Vitória, P., Pereira, S. E., Muinos, G., De Vries, H., & Lima, M. L. (2020). Parents modelling, peer influence and peer selection impact on adolescent smoking behavior: A longitudinal study in two age cohorts. *Addictive Behaviors, 100*(106131).

Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior.* Princeton University Press.

Walden, B., McGue, M., Burt, S. A., & Elkins, I. (2004). Identifying shared environmental contributions to early substance use: the respective roles of peers and parents. *Journal of Abnormal Psychology, 113*(3), 440-450.

Walters, G. D. (2016). Friends, cognition, and delinquency: Proactive and reactive criminal thinking as mediators of the peer influence and peer selection effects among male delinquents. *Justice Quarterly, 33*(6), 1055-1079.

Warr, M. (1993). Age, peers, and delinquency. *Criminology, 31*(1), 17-40.

Warr, M. (1998). Life□course transitions and desistance from crime. *Criminology, 36*(2), 183-216.

Warr, M. (2002). *Companions in crime: The social aspects of criminal conduct.* Cambridge University Press.

Weerman, F. M. (2011). Delinquent peers in context: A longitudinal network analysis of selection and influence effects. *Criminology, 49*(1), 253-86.

Weerman, F. M., & Smeenk, W. H. (2005). Peer similarity in delinquency for different types of friends: A comparison using two measurement methods. *Criminology, 43*(2), 499-524.

Weisheit, R., Falcone, D., and Wells, L. (2006). *Crime and policing in rural and small-town America.* 3rd ed. Long Grove, IL: Waveland Press Inc.

Werner, E. E. (1995). Resilience in development. *Current Directions in Psychological Science, 4*(3), 81-84.

Werner, E. E., & Smith, R. S. (1992). *Overcoming the odds: High risk children from birth to adulthood.* Cornell University Press.

Widdowson, A. O., Siennick, S. E., & Hay, C. (2016). The implications of arrest for college enrollment: An analysis of long□term effects and mediating mechanisms. *Criminology, 54*(4), 621-652.

Wikström, P. O. H. (2007). In search of causes and explanations of crime. In King, R. D., & Wincup, E. (Eds) *Doing research on crime and justice,* (p. 117-39). Oxford University Press.

Wiley, D. E. (1973). The identification problem for structural equation models with unmeasured variables. In: A.S. Goldberger, O.D. Duncan (Eds.), *Structural equation models in the social sciences* (p. 69–83). New York: Academic Press.

Wiley, S. A., Slocum, L. A., & Esbensen, F. A. (2013). The unintended consequences of being stopped or arrested: An exploration of the labeling mechanisms through which police contact leads to subsequent delinquency. *Criminology, 51*(4), 927-966.

Williams, K. R., & Hawkins, R. (1986). Perceptual research on general deterrence: A critical review. *Law and Society Review 20*(4): 545-72.

Wills, T. A. (1986). Stress, coping, tobacco and alcohol use in early adolescence. In S. Shiffman & T. A.Wills (Eds.), Coping and substance use (pp. 67–94). New York: Academic Press.

Wirth, Lewis. 1931. Culture, conflict, and delinquency. *Social Forces, 9*(4): 484-92.

Wright, B. R., Caspi, A., Moffitt, T. E., & Paternoster, R. (2004). Does the perceived risk of punishment deter criminally prone individuals? Rational choice, self-control, and crime. *Journal of Research in Crime and Delinquency, 41*(2), 180-213.

Wright, J. P., & Cullen, F. T. (2004). Employment, peers, and life-course transitions. *Justice Quarterly, 21*(1), 183-205.

Wuthnow, R. (2019). *The left behind: Decline and rage in small-town America.* Princeton University Press.

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods, 51*(1), 409-28.

Young, J. T., Barnes, J. C., Meldrum, R. C., & Weerman, F. M. (2011). Assessing and explaining misperceptions of peer delinquency. *Criminology, 49*(2), 599-630.

Young, J. T., Rebellon, C. J., Barnes, J. C., & Weerman, F. M. (2014). Unpacking the black box of peer similarity in deviance: Understanding the mechanisms linking personal behavior, peer behavior, and perceptions. *Criminology, 52*(1), 60-86.

Zimmerman, G. M., & Messner, S. F. (2011). Neighborhood context and nonlinear peer effects on adolescent violent crime. *Criminology, 49*(3), 873-903.

Zimmerman, G. M., & Vasquez, B. E. (2011). Decomposing the peer effect on adolescent substance use: Mediation, nonlinearity, and differential nonlinearity. *Criminology, 49*(4), 1235-1273.

Zimmerman, M. A., Stoddard, S. A., Eisman, A. B., Caldwell, C. H., Aiyer, S. M., & Miller, A. (2013). Adolescent resilience: Promotive factors that inform prevention. *Child Development Perspectives, 7*(4), 215-20.

Zuckerman, M. (1994). Behavioral expressions and biosocial bases of sensation seeking. Cambridge, UK: Cambridge University Press.